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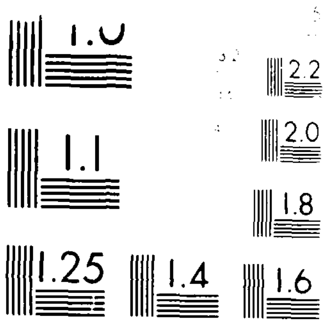

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Final Report For:

OPERATOR ALERTNESS/WORKLOAD ASSESSMENT USING STOCHASTIC MODEL-BASED ANALYSIS OF MYOELECTRIC SIGNALS

A. Madni
C. Conaway
S. Otsubo
Y. Chu

Prepared For:

AIR FORCE OFFICE OF SCIENTIFIC RESEARCH
Bolling Air Force Base
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PERCEPTRONICS

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This report summarizes the research conducted in the second phase of this three-year research and development program directed toward the analysis and evaluation of myoelectric signals (MES) as indicators of operator alertness and piloting workload. The purpose of the study was to investigate the efficiency of stochastic models such as autoregressive (AR), autoregressive-moving-average (ARMA), and autoregressive integrated moving average (ARIMA) models in characterizing the MES under different levels of task-imposed burden.

The implications from this three-year research program are two-fold. Surface myoelectric activity is not a reliable measure of operator alertness. During Phase I, the first autoregressive coefficient of the ARIMA model revealed a significant correlation with task difficulty level. During Phase III, the ¬ weights did not show the same trend. Intramuscular electrodes, on the other hand, that do pick up

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more reliable signatures have obvious drawbacks. Post hoc analysis of the experimental data revealed that the total number of experimental subjects which were constrained by program scope and size were inadequate in terms of producing a statistically significant difference in perceived stress between the single and dual-task groups.

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1. INTRODUCTION

1.1 Overview

This report summarizes the research conducted in the second phase of this three-year research and development program directed toward the analysis and evaluation of myoelectric signals (MES) as indicators of operator alertness and piloting workload. The purpose of the study was to investigate the efficiency of stochastic models such as autoregressive (AR), autoregressive-moving-average (ARMA), and autoregressive integrated moving average (ARIMA) models in characterizing the MES under different levels of task-imposed burden.

The three year program built on the research performed by Madni (1978, 1981), Graupe and Cline (1975) and Graupe, Magnussen and Beex (1977) who established the feasibility of stochastic models in characterizing sampled myoelectric signal waveforms. In particular, the work of Madni has established the feasibility of characterizing myoelectric signals under varying levels of muscle tension and physical fatigue via stochastic models. This program has explored methods for characterizing the myoelectric signal under varying mental stress levels of the human operator.

The research conducted provided a firm analytical and experimental basis for model-based feature extraction by providing techniques for algorithmic improvement in accuracy, by investigating critical issues in pattern variations due to individual operator's behavioral differences, and by providing techniques for symbolic interpretation. The program culminated in the development of a prototype MES analysis system and guidelines for its application in assessing operator stress and/or alertness in various piloting activities.

1.2 Problem Statement

The definition and derivation of objectives measures for assessing workload, attentional demands, or operator alertness in specific piloting tasks has been an area of investigation by several researchers for more than three decades. Myoelectric signals (MES) have been the subject of a search by some researchers (Kennedy and Travis, 1947; Travis and Kennedy, 1947; Kennedy, 1953) for a physiological indication of alertness in piloting tasks. The results of these experiments demonstrated that there appeared to be some correlation between MES properties (e.g., spike amplitude, zero crossings) and human alertness. However, the use of these properties as an indicator of alertness level was never successfully incorporated in a practical setting primarily because of the excessively high false positives in certain tasks. That is, diminished alertness has been identified in many situations when the subject was clearly alert. One plausible explanation for this unreliability in "answers" extracted from MES signatures is that the information content of the original MES waveform is underutilized. In other words, the reliability of features, the information content of the features, and the feature extraction process are critical to the success of the alertness/workload level discrimination process.

1.3 Program Objectives

Several of the program objectives were met in the first phase of the program. These included:

(1) The development and implementation of stochastic model-based signal processing and pattern analysis approaches within the overall framework of the data acquisition and processing system.

(2) The derivation of model structure, feature extraction, and parameter identification processes for constructing MES-based indicators of alertness/workload.

(3) The development of an experimental plan and a representative task simulation and interface.

(4) A pilot experimental investigation.

(5) The evaluation of MES features in terms of their relevance to operator alertness level and/or mental load.

The second phase of the program built on the work resulting from the first phase by enhancing model parameter estimates and algorithm accuracy, investigating experimentally the performance of the model-based feature extraction methods, determining pattern responses to different task characteristics and individual differences, and establishing a rule-based framework for interpretation of the feature parameters. Program objectives met during the second phase of the program included:

(1) The expansion of the ARIMA-based feature extraction process to provide better estimates of the model parameters and to improve computational accuracy of the algorithms.

(2) Improved data collection system to provide speedy global and automatic pick-up of MES signals.

(3) Expansion of the task simulation to include critical air pilot situations where the alertness of the aircrew to high-stress and multiple-task conditions is essential.

(4) Identification of range of feature variations and model accuracy/validity.

(5) Development and experimental use of the extended model/system in extracting indications of operator alertness/load level.

(6) Development of guidelines for operational application of the MES analysis system in air piloting tasks. The guidelines should include: methods of measurements; model structuring; parameter estimation and interpretation techniques; and specification of the system's control and display requirements.

1.4 Technical Approach

Stochastic modeling and time series analysis methods have been extensively used to statistically model the relationship between the amplitude of the signal at different points in time along the entire time history. In this model, the amplitude fluctuations along the timeline are treated as a stochastic process. Stochastic models are particularly well suited as a temporal feature extraction tool for time varying random signals. Such features, because of their high information content, have proven to be diagnostic indicators in applications where purely spectral or ad hoc feature extraction methods have failed (Madni, 1978). The key hypotheses underlying the use of stochastic models as a feature extraction method for alertness level identification were that: (1) at least one of the features will be relatively constant and repeatable for the mental load category and task during which the signal was recorded; and (2) at least one of the nearly constant features for each alertness category/load condition will be distinctly different for each level thus enabling identification of the category.

The stochastic modeling approach for characterizing bioelectric signals is most applicable to model physiological data which possess some or all of the following characteristics:

(1) The data trace is noisy, i.e., data points show random fluctuations in amplitude and are thus amenable to being modelled as a random sequence.
(2) The classification problem is restricted to a finite, previously established, number of categories.
(3) Simpler features extraction methods such as power spectrum analysis, root-mean-square-value estimation, and amplitude level coding fail to provide good separation among the classes.

Other examples of physiological signals amenable to stochastic modeling include: (1) Steady State Electro-encephalograms (EEGs); (2) Visual Evoked Response; and (3) Electro-oculograms (EOGs).

1.5 Findings

The research performed during this three-year program revealed several facts consistent with past research in this field. First, surface myoelectric signals tend to be much too "noisy" to extract consistently stable (i.e., invariant) features from the waveform. Consequently, reliability of the MES signatures was found to be inadequate for reliable discrimination. Past research in this area where relatively stable features were acquired were based on the use of intramuscular Basmajian type electrodes (Madni, 1978). With surface electrodes, trends were observed in approximately twenty percent of the subjects tested. However, the trends were not robust enough to make conclusive assessments. With respect to diagnosticity, the MES pattern associated with the different levels of task difficulty could not be easily separated. Since great care was exercised in electrode placement and contact and in task design, we attribute these results to two key factors:

(1) The change of electrodes from Phase I of the program to Phase II was motivated by shape and size consideration. However it is conceivable that the resulting MES patterns were contaminated by extraneous signals even though the signals looked clean and devoid of 60 hertz interference. The main reason for this conclusion stems from the significantly better results in terms of stable features achieved during Phase I of this program. This argument can account in part for the lack of reliability in the MES signature derived via ARIMA model analysis.

(2) The selected muscle sites, i.e., the frontalis and the trapezius may not be as correlated with operator alertness/workload levels as originally envisioned. This argument accounts in a large part for the relatively low diagnoscity of MES signatures in distinguishing reliably among the different task loading conditions.

The implications from this three-year research program are two-fold. Surface myoelectric activity is <u>not</u> a reliable measure of operator alertness. During Phase I, the first autoregressive coeffocient of the ARIMA model revealed a significant correlation with task difficulty level. During Phase III, the π weights did not show the same trend. Intramuscular electrodes, on the other hand, that do pick up more reliable signatures have obvious drawbacks. Post hoc analysis of the experimental data revealed that the total number of experimental subjects which were constrained by program scope and size were inadequate in terms of producing a statistically significant difference in perceived stress between the single and dual-task groups. A detailed description of findings is presented in Section 6 of this report.

2. BACKGROUND

2.1 Rationale and Hypothesis

The MES, within the context of human performance and workload, has been studied by various researchers over the last three decades. Within the context of human performance, the MES can be potentially used to provide a measure of either activity of the muscles or the tension of the muscles. When workload estimation is involved, data processing of some kind has to be performed on the raw MES data. This processing can range from conventional signal processing and filtering methods to temporal feature extraction and pattern analysis methods.

A number of studies have been carried out to demonstrate the practical value of MES as a measure of task workload and performance quality. Among the earliest research is that of Kennedy and Travis (1947, 1948, 1949) who found that the level of the integrated MES recorded over the supraorbital facial area was closely related to vigilance and tracking performance. Lucaccini (1968) observed similar changes in the integrated forearm flexor muscle MES during simple and complex visual tasks. He also reported that the average intrasubject correlations between MES and performance were significant in both tasks ($r = .21$ and $.30$ in simple and complex tasks, respectively). Stern (1966) found that integrated neck MES rose initially and fell thereafter during easier and more difficult (lower signal frequency) versions of a simple visual task.

It seems from these results that integrated MES voltage is one of the better predictors of vigilance performance, but it has not been universally accepted that MES varies directly with vigilance task performance. Eason, Beardshall and Jaffee (1965) interpreted their results as indicating that sympathetic activity decreases along with Central nervous system arousal and vigilance, but that somatic activity increases as part of a compensatory process. Groll's (1966) conclusions were essentially the same. Yet, judging from their results and the contradictory findings of others, muscle tension, like performance, may reflect both the processes underlying declines in vigilance performance and those acting to counteract it.

For these reasons, stochastic modeling approaches which examine the entire temporal signature, i.e., the whole latency domain, are preferable to ad hoc isolated-feature dependent methods. It is expected that the use of stochastic model-derived features in conjunction with single-features such as P300 component amplitude and latency (e.g., Israel et al, 1980) potentially offer a diagnostic and reliable direction for the assessment of internal operator states.

Jex and Allen (1970) found that rectified and suitable filtered MES recorded from the forearm of subjects showed a decrease in amplitude when subjects changed from a resting to a tracking state. These researchers also found that grip pressure increased with an increase in tracking difficulty. Sun, Keane and Stackhouse (1976) and Stackhouse (1976) found that MES from the forehead and the forearm were correlated with task loading in a variety of aircrew tasks. Madni (1978) found a deterministic correlation between MES reorded during isometric contraction of the deltoid muscle at various load levels and the associated MES stochastic model parameters.

From the foregoing, it appears that MES can potentially provide reliable correlates of operator states such as alertness levels or load; however, in order to achieve this goal, computer-based signal analysis and feature extraction methods must be systematically applied to the MES recordings. Stochastic modeling approaches which examine the entire temporal signature, i.e., the whole latency domain, are preferable to ad hoc isolated feature-dependent methods. It is expected that the use of stochastic model-derived features in conjuction with single-features such as P300 component amplitude and latency (e.g., Israel, Wickens, Chesney and Donchin, 1980) potentially offer a diagnostic and reliable direction for the assessment of internal operator states.

Even with stochastic modeling approaches, the transient nature of ERPs require that a fairly general form of a stochastic model be used, i.e., one that can at least accommodate nonstationarity in the mean of the waveform. Since ARIMA stochastic models are designed to handle nonstationary means, they offer a particularly promising framework for extracting informative features from ERPs.

2.2 Stochastic Models

Stochastic modeling or time series analysis (Box and Jenkins, 1970) have been extensively used to model the statistical relationship between the amplitude of a signal at any point in time and the preceeding amplitudes along the time history. The amplitude fluctuations along the time line are treated as a stochastic process. The future course of the process is presumed to be predictable from information about its past.

Before describing these models, the notation employed will be summarized.

. Let

$$\boxed{\cdots\cdots X_{k-1}X_kX_{k+1}\cdots\cdots\cdot\cdot}$$

be a discrete time series where X_i is the random variable X at time i. We denote the series by [X].

. Let μ be the mean of [X], called the level of process.

. Let [X] denote the series of deviations about μ; that is,

$$\boxed{X_i = X_i - \mu}$$

. Let [W] be a series of outputs from a white noise source with a mean zero and variance σ^2.

. Let B be the "backward" shift operator for the deviation series such that

$$\boxed{Bx_k = x_{k-1}}$$

Hence, $B^m x_k = x_{k-m}$

. Let ∇ be the backward difference operator for the deviation series such that

$$\boxed{\nabla x_k = x_k - x_{k-1} = (1-B)x_k}$$

Hence, $\nabla^m x_k = (1-B)^m x_k$

The dependence of the current value x_k on the past values of x and w can be expressed in different ways giving rise to several different models.

(a) Autoregressive (AR) Models. In this model the current value of x depends on the previous p and x and on the current noise term w. Thus,

$$\boxed{x_k = a_1 x_{k-1} + a_2 x_{k-2} + \ldots + a_p x_{k-p} + w_k}$$

or

$$\boxed{x_k = \sum_{i=1}^{p} a_i x_{k-2} + w_k}$$

The series [X] as defined above is known as the autoregressive process of order p. The name "autoregressive" arises from the model's similarity to regression analysis and the fact that the variable x in an AR model is regressed on previous values of itself.

(b) Moving Average (MA) Model. In the equation for the AR model, x_{k-1} can be eliminated from the expression for x_k by substituting

$$\boxed{x_{k-1} = a_1 x_{k-2} + a_2 x_{k-3} + \ldots + a_p x_{k-p-1} + w_{k-1}}$$

The process can be repeated to eventually yield an equation for x_k as an infinite series in the w's. A moving average model allows a finite number q or previous w values in the expression for xk. This formulation explicitly treats the series as being observations on linearly filtered Gaussian noise. A MA process of order q is given by

$$\boxed{x_k = \sum_{i=1}^{p} b_i w_{k-i} + w_k}$$

(c) <u>Mixed Model: Autoregressive-Moving Average (ARMA) Model</u>. To achieve flexibility in the fitting of actual time series, this model includes both the AR and the MA terms. A (p,q) ARMA model has the form:

$$\boxed{x_k = \sum_{i=1}^{p} a_i x_{k-i} + w_k - \sum_{i=1}^{p} b_i w_{k-i}}$$

In all three models described above the process of generating the series is assumed to be in equilibrium about a constant mean level. Models characterized by such an equilibrium condition are called stationary models. In certain time series data, the level μ does not remain constant, i.e., the series is nonstationary. The series may, nevertheless, exhibit homogeneous or stationary behavior after the differences due to level drift have been accounted for. It can be shown that such behavior can in certain instances be represented by an autoregressive-integrated-moving-average (ARIMA) model.

(d) Autoregressive-Integrated-Moving-Average (ARIMA) Model. The general (p,d,q) model has the form

$$\boxed{\nabla^d x_k = \sum_{i=1}^{p} a_i \; \nabla^d x_{k-i} + w_k - \sum_{i=1}^{p} b_i w_{k-i}}$$

where x_k is the original time series

∇ is the backward difference operator

d is the number of differencing operations performed on the original data

p is the order of the autoregressive terms

q is the order of the moving average terms

$$\boxed{\text{If} \quad Y_k = \nabla^d x_k}$$

$$\boxed{\text{Then} \quad Y_k = \sum_{i=1}^{p} a_i y_{k-i} + w_k - \sum_{i=1}^{p} b_i w_{k-i}}$$

This model is referred to as a general (p,d,q) model referring to a general p^{th} order autoregressive, d^{th} data differencing, q^{th} order moving average process (Box et al, 1970).

2.3 ARIMA Models in MES Characterization

The feasibility of ARIMA Stochastic Model Identification for feature extraction was explored by Madni (1978). The key elements of this study are provided in the following paragraphs.

The experimental data consisted of MES records from the deltoid muscle for different isometric contraction levels. These ranged from 0% to 100% (maximum), where 100% tension is defined as 100% of the force generated at maximum effort, not 100% of MES. The primary assumption in this experiment is that an X% run corresponds to X% of muscle tension which is proportional to abduction, and that the only muscle involved in abduction is the deltoid.

The results of the spectral analysis performed on the experimental data revealed a gradual but definite shift of power to lower frequencies with an increase in muscle contraction. The total power of the signal was found to lie below 2500 Hz. The most significant shift of power to lower frequencies with increasing muscle tension was observed in the frequency band that contained ninety percent of the total power.

ARIMA models were fitted to the MES data recorded for each contraction level. The ARIMA parameters were fitted across the n trials for each contraction level. It was shown that AR terms of the a vector do not change significantly for the 1%, 5%,......,50% tension levels. However, the AR coefficients for the 100% tension level is quite different from those for all other tension levels (both in sign and magnitude). The contraction level ranges (within which the AR coefficients of the ARIMA pattern vector are relatively stationary) that resulted from this experiment were:

(1) 1% through 50% (or 'low') contraction range

(2) 50% through 100% (or 'high') contraction range

Each of these two contraction ranges can be represented by an average pattern vector. A question that arises here is how one can determine, online, the underlying contraction levels from the MES spectral signature. The results from the spectral signature analysis reveal that 90% of the cumulative power was below 400 Hz for the high tension case, but was above 400 Hz for the low contraction level case. This fact provided a useful criteria for determining whether a given MES pattern should be compared to the 'low' contraction pattern vector or the 'high' contraction pattern vector. Details of the online recognition rule may be found in Madni (1978).

3. SYSTEM IMPLEMENTATION AND EXPERIMENTAL SET-UP

3.1 Overview

The system architecture was designed and implemented in parallel with the first series of experiments for assessing the "goodness" of model-derived features in terms of their relevance to operator alertness/workload levels. The primary tool used for performing this assessment in both series of experiments is a computer-based stochastic signal processing and pattern recognition algorithm described in earlier sections.

This section discusses the behavioral issues being investigated through the use of model-based feature derivation/extraction of workload correlates. Workload correlates were primarily gathered through a task simulation based on the Criterion Task Set (CTS) workload test battery developed at AFAMRL (Shingledecker, 1983). The task simulation was altered to some degree to accommodate the experimental hardware constraints and to control the experimental and behavioral variables during the task. Each subject was presented with controlled workload tasks along cognitive processing and motor task dimensions. As the subject performed the various tasks, the MES data was recorded at rest, at the beginning, and near the end of task execution. At the conclusion of each task, model outputs, subject performance, and subjective rating comparisons were made between levels of task loading and among the various task dimensions.

3.2 ARIMA Model Identification of MES

The key research problems forming the basis of this study and underlying the use of stochastic models as a feature extraction method are described in the following paragraphs.

The fundamental hypothesis forming the basis of this study is that MES recorded from selected muscle groups are correlated with internal states of the human operator (e.g., alertness level or mental load) and that a suitably selected/designed feature extraction method is capable of uncovering the underlying operator state in terms of invariant features associated with the MES. It was our hypothesis that stochastic model characterization of the MES waveforms is potentially capable of "capturing" features that are both repeatable and diagnostical. Repeatability implies that there is at least one parameter in the stochastic model characterization of MES data that is constant or near-constant for each underlying level of alertness or load in a given task. Diagnosticity implies that these nearly invariant features are sufficiently different for each level of alertness, thereby allowing identification of the underlying operator state. The specific stochastic model selected for MES characterization is the ARIMA model.

As shown earlier, an ARIMA model for a general time series has d levels of differencing, p autoregressive coefficients, and q moving average coefficients as shown in the equation below:

$$\boxed{\nabla^d Z_t - \phi_1 \nabla^d Z_{t-1} - \ldots . \phi_p \nabla^d Z_{t-p} = a_t - \theta_1 a_{t-1} - \ldots . \theta_q a_{t-q}}$$

where $\nabla^d Z_u$ is the d^{th} difference of the time series at time u

a_u is the zero mean, normally-distributed random noise at time u

ϕ_i is the i^{th} autoregressive coefficient

θ_i is the i^{th} moving average coefficient

Determination of p, d, and q is a three step procedure. The first step of the ARIMA modeling as provided by Box & Jenkins (1970) is to identify p,d, and q. The specific software module associated with this step calculates autocorrelations and partial autocorrelations for different levels of data differencing. These autocorrelations and partial autocorrelations provide an insight in selecting p,d, and q of the ARIMA model. To determine d, one looks at the autocorrelations for a given level of differencing and observes whether or not they "die out" rapidly. If they do, the given level of differencing is adequate; if not, additional differencing operations are required until this constraint is satisfied. The smallest level of differencing for which the autocorrelations die out rapidly is taken as the optimal level of differencing, d.

To determine p and q we look at the autocorrelations and partial autocorrelations for the selected level of differencing. Box and Jenkins summarize this approach as follows:

> "Briefly, whereas the autocorrelation function of an autoregressive process of order p tails off, its partial autocorrelation function has a cutoff after lag p. Conversely, the autocorrelation function of a moving average process of order q has a cutoff after lag q, while its partial autocorrelation tails off. If both the autocorrelations and partial autocorrelations tail off, a mixed process is suggested. Furthermore, the autocorrelation function for a mixed process, containing a p^{th} order autoregressive component and a q^{th} order moving average component, is a mixture of exponentials and damped sine waves after the first p-q lags. Conversely, the partial autocorrelation function for a mixed process is dominated by a mixture of exponentials and damped sine waves after the first p-q lags."

Once p, d, and q are selected, we proceed to the second stage of the model identification process. The purpose of the second stage is to come up with initial estimates of the autoregressive and moving average parameters. These initial estimates are then used by the third stage of the model in generating final estimates of the autoregressive parameters. The result of this three-stage process is a feature vector consisting of parameters that parsimoniously characterize the original MES time series data.

3.3 ARIMA Software (AUTOBJ) and Functional Description

The ARIMA modeling of MES was based on a recently released program, AUTOBJ (an automatic Box & Jenkins modeling procedure) developed by Automatic Forecasting Systems, Inc. for use on an IBM PC/XT with an 8087 floating-point chip. The previous system, the COSMOS/UNIX system, did not support a floating-point hardware. Consequently, it was necessary in phase one of the effort to develop a batch mode program that allowed the experimenter to specify up to 25 files representing 25 experimental sessions and process all the records in these files. AUTOBJ, the software on the IBM PC/XT with the supporting floating-point hardware does not require this batch processing. The key features of AUTOBJ are described in Table 3-1.

TABLE 3-1
KEY FEATURES OF AUTOBJ

- Computes the optimal level of differencing.
- Easily handles a mixed model (ARMA) (the in-house system generally set q to zero).
- Discards ϕ and θ weights of low significance.
- Computes - weights as opposed to AR parameters for comparison.

The models obtained for the software used during phase one were generally AR models whose coefficients were directly comparable, while the models produced by AUTOBJ that have differing values of p, d, and q may not be directly compared. This problem of incompatibility was solved by using the model to generate π weights and using the π weights for comparison rather than the model feature vector.

Any ARIMA (p,d,q) model can be expressed as an infinite series of weights as follows:

Take the general ARIMA (p,d,q) model,

$$\boxed{(1-\phi_p(B))(1-B)^d Z_t = (1-\theta_q(B))a_t}$$

Divide both sides by $(1-\theta_q(B))$ to yield,

$$\boxed{\frac{(1-\phi_p(B))(1-B)^d Z_t = a_t}{(1-\theta q(B))}}$$

The resulting polynomial coefficients of the potentially infinite order polynomial in B represent the - weights. If q=0, then the polynomial is of order p and identical to the ϕ p(B) polynomial. It is important to truncate the o weights after some number such as (p+d+q) to parsimoniously represent the time series.

With its floating-point hardware support and automated identification procedure, the AUTOBJ program was a very powerful tool for the purposes of this investigation.

AUTOBJ allows efficient implementation of Box & Jenkins models and produce time series identifications. Starting with raw data, the program's algorithm follows the model building methodology described by Box and Jenkins -- that of tentative model identification, parameter estimation and diagnostic checking (for the purposes of this project, only the model identification was employed). While requiring only minimal input by the user, the program is quite flexible in allowing for optimal user control. AUTOBJ provides a quick, convenient and powerful means for developing ARIMA models for the MES time series data.

To be more explicit, AUTOBJ consists of two stages. In the first stage the system queries the user for information concerning the data. Stage two involves the execution of the statistical ARIMA modeling analysis based on the data introduced in stage one. The output of the program is a detailed printout of the feature vectors calculated from the modeling process of the time series identification. These vectors are later used to evaluate the correlation of the MES signature to the performance measures from the various tasks.

3.4 ARIMA Model Implementation

The AUTOBJ software package was used to extract the time series identification from the experimental data. It took approximately 30 minutes of run-time to process each file consisting of 1000 data points. The resulting printout for two subjects is shown in Appendix D. The modeling results include univariate model parameters (such as the mean and the ARIMA coefficients), residual statistics and pi-weights.

3.5 Signal Integrity Plotting Package

The first series of experiments during phase one did not incorporate explicit means of verifying the integrity of the signals being measured. In order to alleviate this problem, a graphics package was developed on the IBM XT to plot the data sampled from both the frontalis and trapezius muscles.

The graphics package, written in C programing language, is customized to the data formats of each new series of experiments. The first one hundred characters of each data file is reserved for a descriptive header. This is followed by 1000 integers in ASCII format.

Three variables are presented to the user with this package: vertical reduction, horizontal magnification and the number of data files to plot. The maximum screen resolution that could be achieved on the IBM XT using a Tecmar Graphics Master Card was 640x200. The flexibility resulting from the vertical reduction and horizontal magnification allows the user to scale the graph within these screen limits. The vertical reduction allows the user to contract the graph along the y-axis in order to ensure that it fits within the screen boundaries. The horizontal magnification allows the user to expand the graph along the x-axis, where the number of data points plotted equals 640/(horizontal magnification). Either one or two data files are plotted along with their respective descriptive headers.

3.6 Communication Interface

Two separate communication interfaces are used in the experimental setup. The interface between the data acquisition system and the IBM XT is used both for the transfer of messages regarding sampling variables to the data acquisition system and the transfer of the sampled data itself. The interface between the Apple IIe and the IBM XT is used for the control of the tasks presented to the subject.

The line between the IBM XT and the data acquisition system is an IEEE-488 bus. This line can transfer data at rates up to three hundred megabytes per second. The IEEE-488 interface to the data acquisition system is built into the system while the interface to the IBM XT had to be purchased separately. This consists of a plug-in card and related software which can be used with applications written in 8086 assembler, Basic and C.

The connection between the Apple IIe and the IBM XT is a standard RS-232 line configured for 9600 baud, even parity, 1 stop bit and a 7 bit word.

3.7 Hardware and Instrumentation

3.7.1 System Selection. The COSMOS computer initially selected for system control and data analysis functions was found to be too limited for our purposes in a number of areas. First, the available A/D cards for the COSMOS (used for amplifying and digitizing the analog myoelectric signals for input to the computer) were too limiting in the control of parameters such as amplification gain, sampling frequency, number of data input channels, etc. Additionally, the lack of graphics capability of the system prevented us from observing the actual signals acquired for integrity. The general unavailability of peripheral devices (e.g., floating-point hardware, graphics hardware) for this particular machine initially forced us to design the experiment around hardware limitations. Therefore, a decision was made to re-analyze the hardware requirements and replace the COSMOS with a different system which offered enough flexibility to handle most any contingency which could occur over the course of the program. Among the requirements of this system were (1) floating-point hardware support, and (2) graphic display capability. Initially, an additional requirement was the availability of an appropriate "C" compiler so that the ARIMA model software used in the first phase of the program could be easily transported to the new computer. This requirement later proved unnecessary since the computer chosen to replace the COSMOS had available to it a commercial model package called AUTOBJ which automated the modeling procedure and improved on some inadequacies of the original software. AUTOBJ was suitably modified for Automatic Forecasting, Inc. for use as a feature extraction tool for our purpose.

An IBM PC/XT microcomputer was selected for both data acquisition and executing the application software. While this 8088 based machine, in general, is not as powerful as the 68000 based COSMOS UNIX system, it offered the advantage of widely available peripheral hardware and software items which were added resulting in an application-specific configuration. The system (Figure 3-1) was configured as follows:

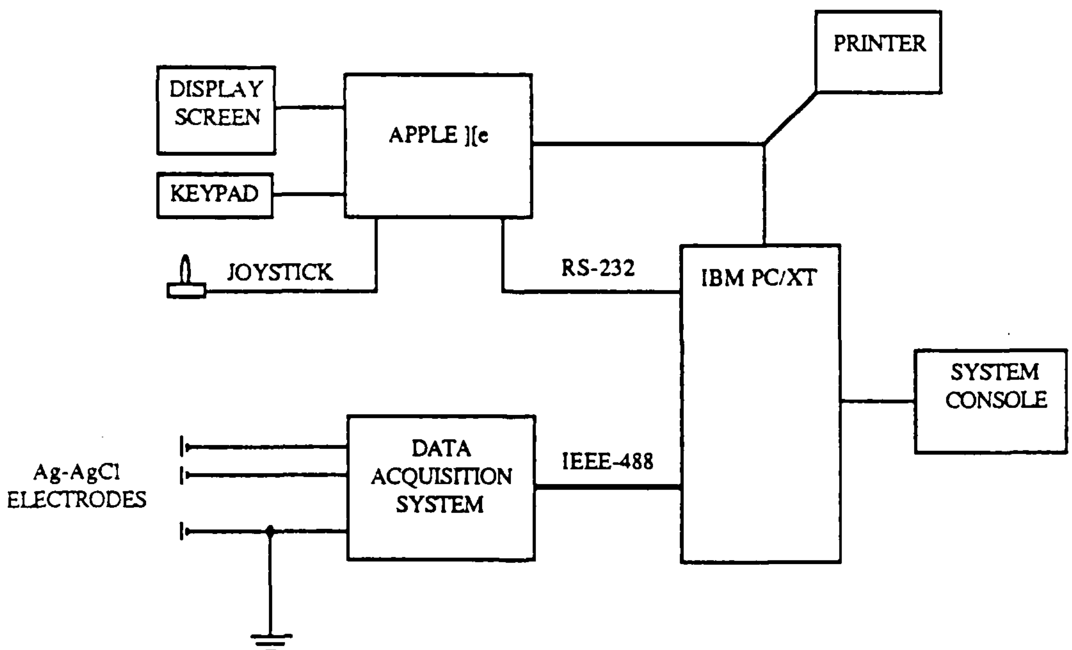


FIGURE 3-1.
SYSTEM CONFIGURATION

- RS-232, IEEE-488, and Centronics interfaces
- 8087 numeric coprocessor
- Trans Era MDAS 7000 data acquisition system
- Tecmar graphics card
- Amdek high resolution monochrome monitor
- Apple IIe with graphics card, serial port, joystick
- Okidata dot matrix printer

3.7.2 Acquisition System. A data acquisition system (DAS) was required to sample the myoelectric signals. The system had to impose as few limitations as possible regarding sampling speed, resolution, variable sampling windows, storage, etc. Furthermore, cost was to be kept to a minimum within program budgetary allocation.

Myoelectric signals have a bandwidth ranging from 25 Hz to approximately 5Khz. However, all the necessary information for our purposes lies within the bandwidth of 25 Hz to 500 Hz. Thus, in accord with Nyquist's sampling theorem the DAS was required to sample at a minimum of 1000 samples per second.

The amplitude of myoelectric signal obtained from a standard electrode varies from 100 V to approximately 5mV. A system which is not sensitive enough for this range of signals would need to have the signals preamplified before they are digitized. This in turn would increase the cost, the complexity and the noise introduced into the system.

A minimum of 2 analog inputs had to be present in the system. True simultaneous inputs would be an advantage in that any possible correlation between the 2 channels could be investigated with more accuracy.

The system required a software package which made available to the user an easy and fast method of CALLing assembly language subroutines from C to handle the I/O and sampling functions.

Many systems were investigated for our purposes. However, only one system fulfilled all the important requirements. TransEra's Model 7000-MDAS is a stand-alone data acquisition system based on the Motorola 68000 micro-processor. The basic processing and Control Unit consists of: 16 slot chassis, basic power unit, 10MHz 68000 processor card with timing module and real-time clock, 2 RS-232 serial ports, 1 IEEE-488 interface port, 22K of static RAM and a 64K firmware module.

Two upgrades purchased with the system were a 16-bit A/D, D/A conversion card which includes 8 programmable gains from 1 to 128 and a low-level $\pm$0.1V, differential analog input module which provides up to 4 isolated simultaneous inputs.

This system has a resolution of approximately 3.05 V per bit with a gain of 1 and has a maximum sampling rate of approximately 48000/(number of channels) samples per second.

3.7.3 <u>Electrode Selection</u>. As discussed in our interim report (Madni, Chu, Otsubo and Purcell, 1984), the Motion Control electrode packages were originally selected for use based on the high-performance characteristics of their integral signal pre-amplifier. However, these electrodes were physically too large to allow for placement on some potentially useful sites (e.g., forehead). Additionally, the sensitive CMOS circuitry used in the design of the pre-amplifier was extremely susceptible to static discharge induced failure with no simple means of failure indication short of experiencing signal degradation.

It was decided that silver/silver chloride "button" type electrodes along with an external high-performance pre-amplifier would be more suitable for our purposes. The characteristics of the VIVO Metric silver/silver chloride electrodes in summarized in Table 3-2.

TABLE 3-2

CHARACTERISTICS OF VIVO METRIC
SILVER/SILVER CHLORIDE ELECTRODES

- Sensor Dia.:	4mm
- Housing Dia.:	7.2mm
- Overall Height:	6mm
- Electrode Cavity:	1mm deep
- Lead:	1m shielded cable

3.7.4 Electromagnetic Interference. Our preliminary study had indicated that 60 Hz interference was contaminating the myoelectric signal. To this end, we constructed a Faraday cage (a grounded, wire-mesh cage) within the room in which a subject could sit while performing a task, essentially shielding him from extraneous R-F interference. Any remaining EMI was removed by using differential electrodes and by grounding the subject.

4. EXPERIMENTAL STUDY

4.1 Overview

The phase one series of experiments were designed to assess the "goodness" of stochastic model-derived features pertaining to operator alertness and workload levels. In that study, behavior variability and hardware limitations prevented totally reliable measures to be gathered from subjects. To alleviate these problems, more stringent experimental design and methodologies were developed to improve experimental control and circumvent the hardware limitations observed during the initial series of experiments.

This section describes the new experimental procedures and the tasks involved in deriving workload correlates. The rationale for changing the tasks, variables and procedures from the original series of experiments, was so that workload performance and perceived stress could be measured more reliably with model-derived MES features.

4.2 Experimental Hypotheses and Test Procedure

The major effort of this program was to be able to predict perceived workload levels from model-derived MES features. To predict workload levels, these MES features have to be reliable and diagnostical to infer appropriate operator states. Two hypotheses, which are characterized as "reliability" and "diagnosticity," were investigated in this study. These hypotheses are:

- Reliability - A minimum of one set of values in the ARIMA model provides invariant or near-invariant pattern values for each subject within a predetermined underlying level of mental load for a given task category, thus achieving "reliability".

o <u>Diagnosticity</u> - Each level of task difficulty has its own distinct pattern, providing a "diagnostic" feature for predicting operator wokload/altertness with model-derived MES features.

To ascertain the reliability and diagnosticity of MES-derived features, several issues were investigated. The first involved detecting at least one set of values in the ARIMA model for each underlying loading/alertness level, subject, muscle site, and task level. To determine this, model coefficients and their related pi-weights were examined for invariance across multiple samples within trials and across multiple trials. If values were found that satisfy the necessary invariant conditions, they were then considered "reliable". These reliable features must also have been sufficiently different in magnitude for each level of the task, to exhibit the attribute of "diagnosticity."

4.3 Experimental Tasks

The original series of experiments were based on simulating a subset of the Criterion task Set (CTS) workload test battery that was developed at AFAMRL (Shingledecker, 1983). These experiments were based on the degree to which they satisfied the requirements of: (1) validity and reliability, (2) flexibility and quantifiability, (3) memory, (4) mental mathematics/reasoning, and (5) choice reaction time. Unfortunately, data from only one subject was used to validate task parameters. Thus, the tasks used in the original experiments were not stringently pretested and validated to correlate to the desired levels of "low" and "high" workload levels; the low difficulty level tasks may have been too easy for the subjects, generating boredom, and the high levels may not have actually represented a higher task-imposed of "stress". There were observed differences in performance and subjective ratings between the high and low levels of task difficulty, but all subjects seem to exhibit boredom and fatigue due to the long experimental sessions and the repetitive task performance required of them. Thus, in the pilot set of experiments, instead of experiencing different levels of stress, subjects were experiencing boredom and fatigue.

Additionally the original tasks were discrete, independent task components, rather than integrated task situations to match the Criterion Task Set (CTS) under development at AFAMRL. This minimized the external validity of the tasks.

To alleviate these problems, a new set of tasks was developed to:

- o Minimize the fatigue and boredom that resulted from the first series of experiments;
- o Achieve a higher level of external validity;
- o Represent validated task levels of low and high stress.

The new set of tasks was developed, based on the objective that when given a primary task at a comfortable pace, adding a secondary task will increase the level of difficulty of the total task. Thus, the perceived stress experienced by the subject should theoretically increase. We first analyzed the basic CTS and selected a subset to employ as our experimental tasks.

The overall CTS included the following task components:

(1) Perceptual tasks

- o Probability monitoring task
- o Auditory monitoring task
- o Visual target search task

(2) Central Processing Tasks

- o Memory tasks - memory update, memory recall
- o Manipulation and comparison tasks - linguistic processing, mathematical computation, spatial pattern identification
- o Reasoning tasks - analogical reasoning and grammar
- o Planning and scheduling - flight assessment and supervisory control

(3) Motor tasks

- o Critical tracking task

A subset of the CTS was selected from existing tasks previously researched and validated at AFAMRL. These task dimensions included a motor task (critical tracking) and a perceptual task (auditory monitoring).

The two tasks used in this series of experiments are described in the following paragraphs.

Critical Tracking Task

The critical Tracking Task was developed as the primary task. In this task the subjects were required to track a target on a computer display screen by controlling a "site" object with a joystick. The subject was directed to track and surround the target with the site, as the target randomly moved around the screen. Performance was based on the average distance between the site and target over the entire session. The more control the subject maintained over the tracking task, the lower the average distance recorded. This task was developed to represent the desired level of "low" stress.

Critical Tracking Task With Added Auditory Monitoring Task

The same Critical Tracking Task was then combined with a secondary auditory monitoring task. This second task required the subject to respond to an auditory tone by pressing a button on top of the joystick. The tones were intermixed so that one tone represented signals and a different tone represented "noise". The subject was required to distinguish the signals from the "noise" by pressing the button only when the signal was heard. The subject was required to respond within 1/2 second from the time the signal was presented. If no response was made within that time, an omission error (a "miss") was recorded. If the subject pressed the button when no tone was presented, a commission error (a "false alarm") was recorded. This monitoring task was presented to the subject with the primary critical tracking task, thus representing a more stressful task than the primary task alone.

4.4 Experimental Variables

The experimental design utilized a within-subject repeated measures design. The following independent variable was tested:

- o Task loading - two levels of difficulty or "stress"

  (1) Critical tracking task only ("low" stress)
  (2) Critical tracking task + auditory monitoring tasks ("high" stress)

The dependent variables gathered from the varying task loading situations were:

- o Performance measures

  (1) average distance between the site and target for the critical tracking task
  (2) auditory monitoring responses, (errors of omission and comission)

- o Subjective measures of effort and stress - gathered from post-test questionnaires
- o MES data gathered through the data acquisition system

In the initial series of experiments there were two task categories and two levels of task difficulty.

- o Task category - two types

  (1) Central processing tasks
  (2) Motor tracking tasks

- o Task loading - two levels of difficulty

  (1) Low load
  (2) High load

We attempted to stay within the same criteria established in the first series, i.e., CTS implementation utilizing two levels of stress. The only major change was the integration of the task categories of a perceptual (auditory) and a motor tracking task together, to achieve a higher level of external validity. We also employed the use of secondary task loading to validate the assumption that presenting an additional task places higher cognitive load on the subject, thus increasing his perceived "stress."

This probe-reaction-time technique has been utilized with notable success in uncovering resource demands for various perceptual/motor and cognitive tasks (Ells, 1973; Posner & Bois, 1971; Posner & Keele, 1969).

To validate the two levels of "stress", pilot studies were performed. Initially, five test subjects were presented seven varying levels of difficulty for the critical tracking task. They were given 30 seconds to perform each level, from the easiest (Level 1) to the most difficult (Level 7). Each test subject practiced and became familiar with all the levels. Each was then given the opportunity to move the level of difficulty up or down by pressing the up-cursor (increases the difficulty level) and down-cursor (decreases the difficulty level) on the computer keyboard. They were told to reach the level at which they felt most comfortable, i.e. not too easy and not too difficult. We assumed that this level would represent the "low" stress level. Three of the test subjects chose level 4, while two subjects chose Level 5, thus we established Level 5 as the level of "low" stress, to minimize the problem of boredom and fatigue that was found to occur in the first series of experiments. We again tested the pilot subjects on the task only at Level 5, and all agreed that it was comfortable level. Those who initially selected Level 4 as the comfortable level could not tell the difference once given the task at Level 5, thus, we maintained Level 5 as the established level of "low" stress.

To find the appropriate level for the secondary task of auditory monitoring, we again conducted pilot studies in which the same test subjects performed the same critical tracking task (Level 5) with varying levels of auditory monitoring (Levels 1-7). Test subjects again were able to practice the critical tracking plus auditory monitoring task to become familiar with all the levels. Next they were given the opportunity to control the levels of auditory monitoring by pressing the up-cursor (increasing frequency of signal and noise presentation) and the down-cursor (decreasing frequency of signal and noise presentation). Subjects were told to maintain the level at which they felt comfortable, i.e. not too easy and not too difficult. All subjects chose Level 4. This task was to represent the level of "high" stress, thus we increased the actual auditory monitoring task to Level 5. We attempted to increase the difficulty by two levels (to Level 6), but discovered that the signals were presented in a predictable pattern. this made it easier instead of more difficult to respond. Consequently, we maintained the auditory presentation of Level 5 as the established level of "high" stress.

We then presented both tasks to all test-subjects, gathered performance and subjective data, and found that there was an observable difference between the "low" stress and "high" stress task performances based on the average distance from site to target on the critical tracking tasks, and on the subjective responses to the amount of effort exerted and stress perceived.

4.5 Muscle Site Selection

Existing literature (Madni, Chu, Otsubo, and Purcell, 1984) suggests a number of muscles (frontalis, trapezius, splenius, temporalis, masseter, brachioradialis) which undergo sporadic, potentially diagnostic activity during high workload situations. Our new data acquisition system gave us the capability of acquiring data from multiple muscle sites, and our new electrodes were of a small enough size to permit judicious placement. However, the additional processing time involved in modeling the data from each additional muscle restricted us at this time to a maximum of two sites. The frontalis and trapezius muscles were chosen.

4.6 Subjects and Procedures

In this phase of the program, 12 male subjects were recruited from the local university, and from the available Perceptronics pool of volunteer subjects. Subject ages ranged from 19-35 years old. All had at least a high school diploma and some experience with using computers. A 2X2 within-subject repeated-measures design was employed. Each subject performed the two tasks twice. After they completed each task, they were given a questionnaire (See Appendix C) to complete regarding their subjective evaluations of the effort expended and the difficulty of the tasks.

In this phase of the program, several major changes were implemented. Before performing the actual experiment, several pilot studies were conducted to investigate the validity of the tasks to be presented. Upon examining the results of the pilot studies, we were able to substantiate the expected differences between the two levels of task difficulty based on task performance and perceived stress.

The original series of experiments attempted to represent low and high levels of difficulty by isolated, discrete tasks. By presenting subjects with different tasks, there was no way of validating whether the tasks used were actually of varying degrees of difficulty or whether they were just different in task type. that is, it was more clear whether the tasks really fell as different points on "level of difficulty" continuum. To correct for this undefined task variability, the method of secondary task loading was used; an auditory monitoring task was added to the primary critical tracking task. This procedure insured that if there was a difference between the primary task ("low" stress task) and the primary plus secondary task ("high" stress task), then it must be due to the additional cognitive load imposed by the secondary task (see Knowles, 1963).

We also recruited 12 subjects participate in the experiment, compared to only 3 subjects in the initial phase so that the statistical power of the experiment would be increased. The results from only three subjects may have been due to chance. Increasing the number of subjects would provide a greater probability that the results would demonstrate statistically significant differences.

The total time required of each subject was 1 to 1-1/2 hours. This is vastly different from the two to three sessions required of them in the initial series of experiments. Reducing the amount of experimental time minimized the probability that the subjects were bored and fatigued with the experimental procedure, and consequently, reduced the probability that physiological measures would be confounded.

Each subject was asked to read the instructions (Appendix A) explaining the experimental procedure. Subjects were encouraged to ask questions as they read the instructions to ensure that they understood the tasks. They were then requested to read and fill out a "personal information fact sheet" and "consent to act as an experimental subject" form. The active electrode assembly was then attached above the (frontalis muscle), and to the subject's upper back (trapezius muscle), running parallel to the muscle fibers. A third "ground" electrode was positioned near the elbow. All electrodes were placed on the subjects' non-dominant side (right-handed subjects had the electrodes positioned on the left arm, and vice versa). Subjects were given an orientation and practice session lasting 5-10 minutes to minimize the learning effect that could occur during the experiment itself. The practice session was concluded when the subjects produced comparable scores on two successive trials for each task. the subjects were then instructed to sit comfortably upright in the chair and cautioned against moving the side of their bodies to which the electrodes were attached. At this time, a sample time series of data was recorded for subjects representing their "At rest" state. At the end of each task, subjects were asked to fill out a questionnaire of subjective ratings and post-experimental comments. After completing this form, subjects rested for a few minutes before the next task was presented. All subjects were given two trials for each task in a counterbalanced order.

Each experimental task lasted 200 seconds. During each trial, data sampled at 1 Khz was collected in 1000 msec windows spaced 30 seconds apart in the last 45 seconds of the trial. This data collection scheme allowed us to evaluate feature reliability both within and between trials.

4.7 Performance Measures

The performance measure of average distance between site and target was gathered so that one common performance measure could be compared between both tasks. In the original series of experiments, the performance measures for low and high-stress tasks differed, making it difficult to reliably determine the meaningfulness of performance differences observed.

The performance measures collected during the experimental trials were:

Critical Tracking Task -

o Average distance between site and target - the average distance measured over 10 second intervals between the random target and the site controlled by the subject

Critical Tracking Task + Auditory Monitoring Task -

o Average distance between site and target - the average distance measured over 10 second intervals between the random target and the site controlled by the subject

auditory response accuracy - the correct responses (hits), omissions (misses) and commissions (false alarms) made by subjects to the auditory "signals"

These performance results were recorded and printed for each task (Appendix D).

Subjects were also requested to fill out a questionnaire after each task was completed. the questionnaire required that subjects rate (on a sliding scale) various items related to: (1) their perception to task difficulty, and (2) their perceived level of effort (Appendix C).

The results of the performance measures and subjective ratings along with the statistical and pattern analysis are discussed in Section 5.2.

5. EXPERIMENTAL RESULTS AND DATA ANALYSIS

5.1 Overview

This section discusses the subjective responses, objective performance data and objective MES measurements that were collectively analyzed in order to identify ARIMA features for varying levels of stress and/or operator workload. Included is a discussion of the trends between tasks that were identified and conclusions that were drawn from the ARIMA model-based analysis.

5.2 Task Performance and Subjective Ratings

Analysis of task performance was made by comparing the average distance between the site and target between the two tasks. These results indicate that an observed difference exists between performance on the two tasks (Figure 5-1). Despite the fact that these differences were statistically significant (paired 5-test, $p \geq .05$), 75% of the subjects' performance dropped from the single to the dual task situation. With an increased number of subjects, and perhaps a greater discrepancy in difficulty levels of the single and dual tasks, it is reasonable to expect that statistical significance would have supported the resulting observed performance differences. The observations showed that 9 subjects out of the 12 performed worse on the dual task (critical tasking + auditory monitoring task). This observed difference may be an indication that the dual task may have been perceived as more stressful.

Questionnaire responses were then analyzed to ascertain differences between the "perceived stress" levels on the two tasks. The pertinent questions relating to perceived stress were:

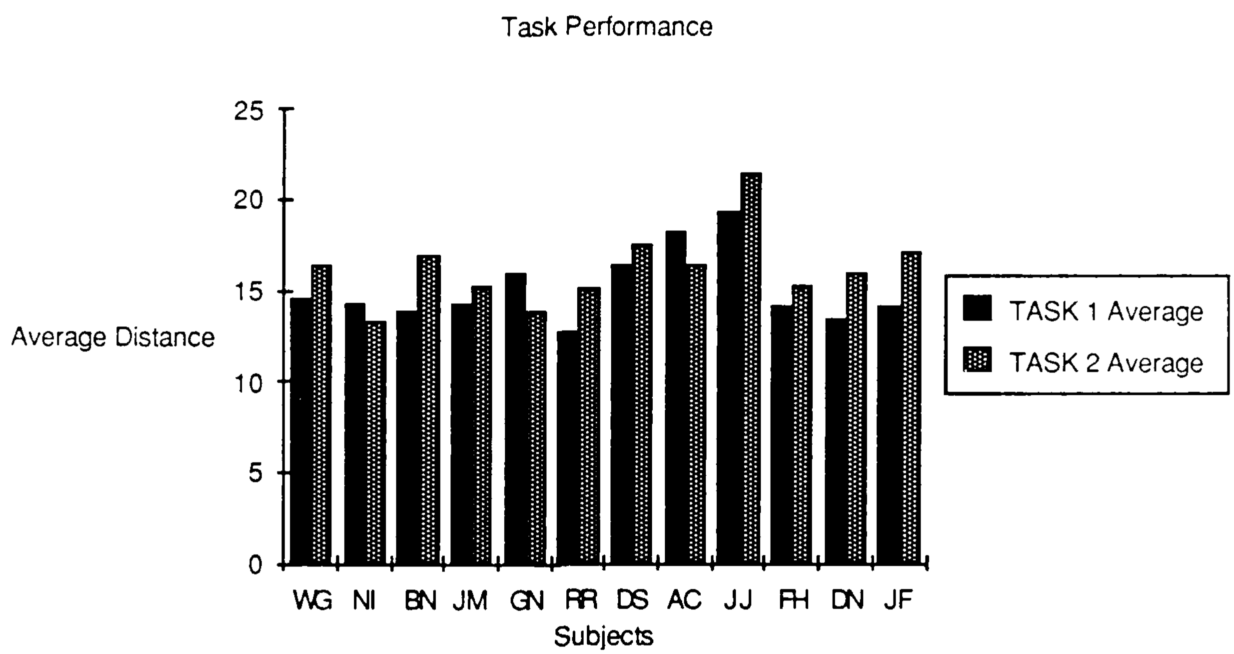


FIGURE 5-1.
TASK PERFORMANCE

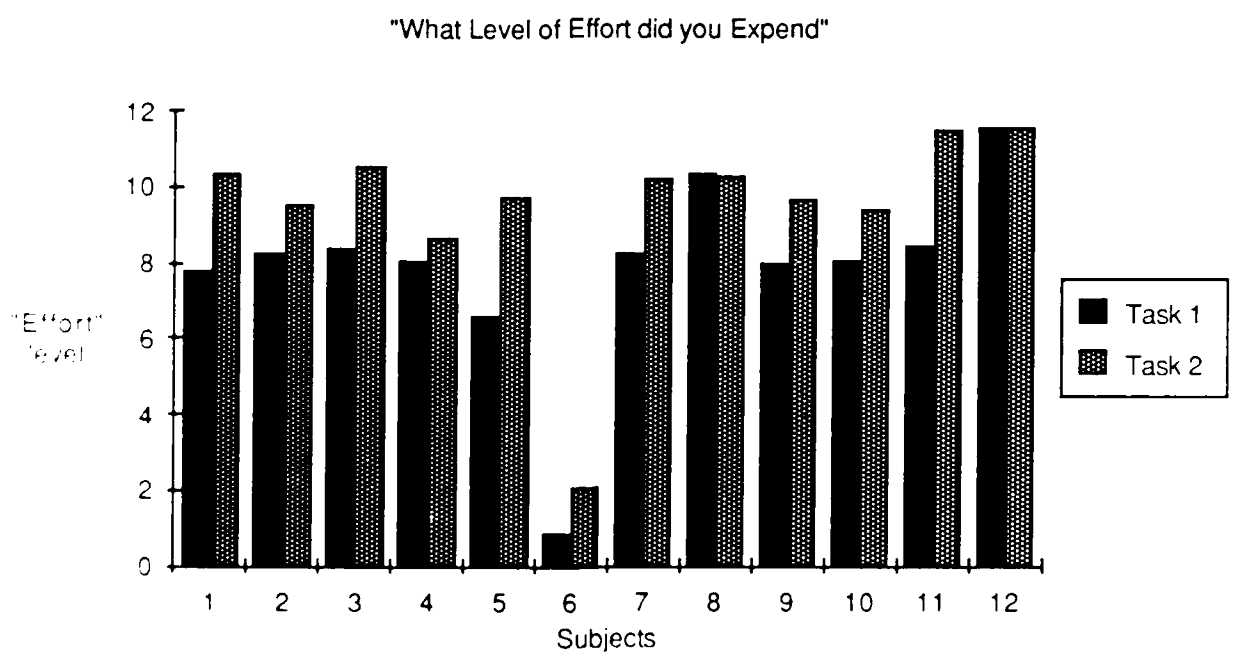


FIGURE 5-2(a).
QUESTIONNAIRE RESPONSES TO "WHAT LEVEL OF
EFFORT DID YOU EXPEND?

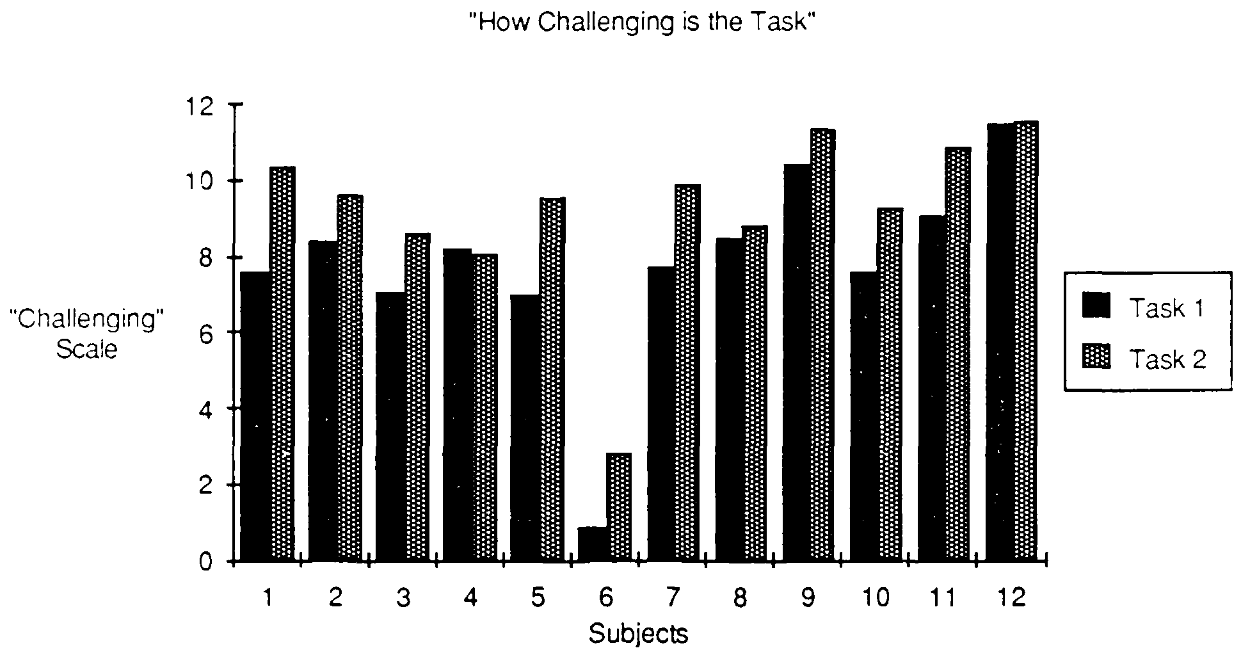


FIGURE 5-2(b).
QUESTIONNAIRE RESPONSES TO "HOW
CHALLENGING IS THE TASK?"

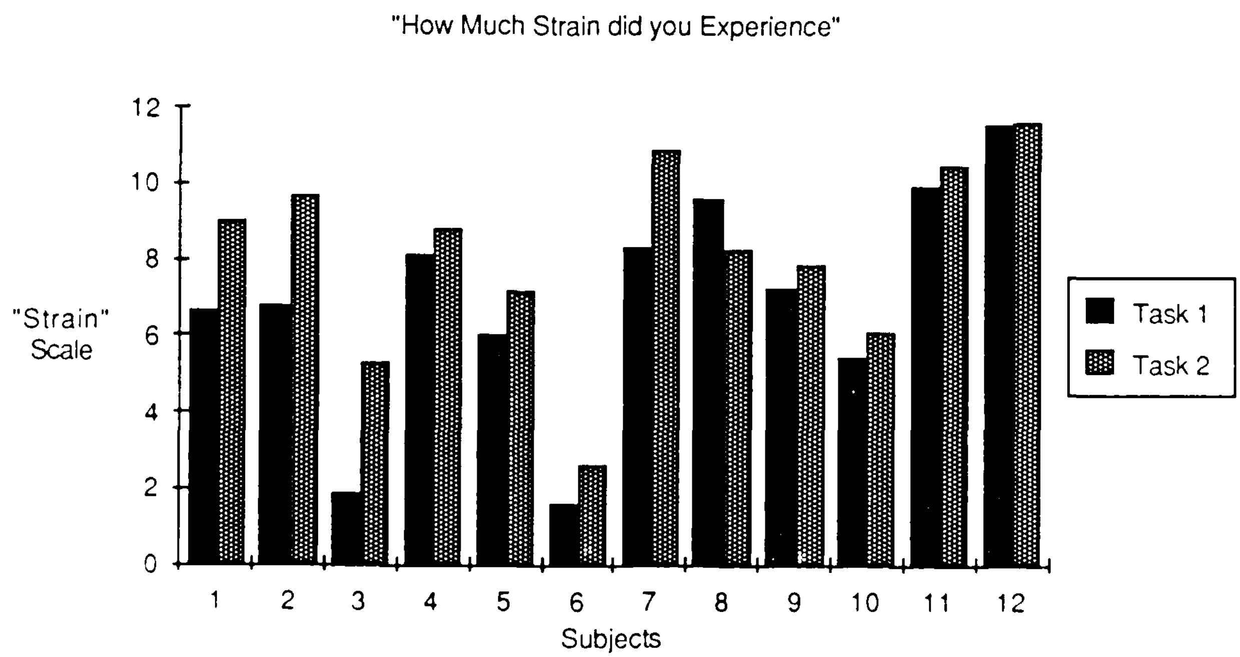


FIGURE 5-2(c).
QUESTIONNAIRE RESPONSES TO "HOW
MUCH STRESS DID YOU EXPERIENCE?"

- o "What level of effort did you expend?"
- o "How challenging was the session?"
- o "How much strain did you experience during the session"

Comparisons between the two tasks exhibited significant differences in response for these questions (paired t-test, $p \leq .005$; Figure 5-2). These differences indicate that increased "perceived stress" was experienced during the dual task, even though there were no statistically significant differences in task performance.

5.3 Results of MES Feature Extraction

MES sampling was conducted a total of nine times for each subject, once at rest before any of the tasks began and twice during each task for both muscles. Each file of MES data was stored and subsequently plotted on the CRT. Samples of these measurements are shown in Figures 5-3 and 5-4 for subjects JJJ and AXC.

The ARIMA analysis, a result of the AUTOBJ software implementation, was conducted for each of the files stored. Sample outputs for subject JJJ and AXC are shown in Appendix D. Modeling results included univariate model parameters, residual statistics and pi-weights for each file. The univariate model parameters included autoregressive, moving average and trend constant parameters. For each of these a factor, lag, coefficient and T-ratio value was extracted. The residual statistics included the sum of squares, mean square, R-squared, degrees of freedom and number of residuals. Univariate models were expressed as pi-weights (weighted sum of the past plus a random shock). The general form of the model expressed by the pi-weights is:

$$Z(t) = \text{Constant} + P_i(1) \cdot Z(t-1) + P_i(2) \cdot Z(t-2) \ldots + P_i(n) \cdot Z(t-n)$$

where:

n is number of lags

t is time

Pi(n) is the value of lag at n

Z(t) is the pi-weight at time t

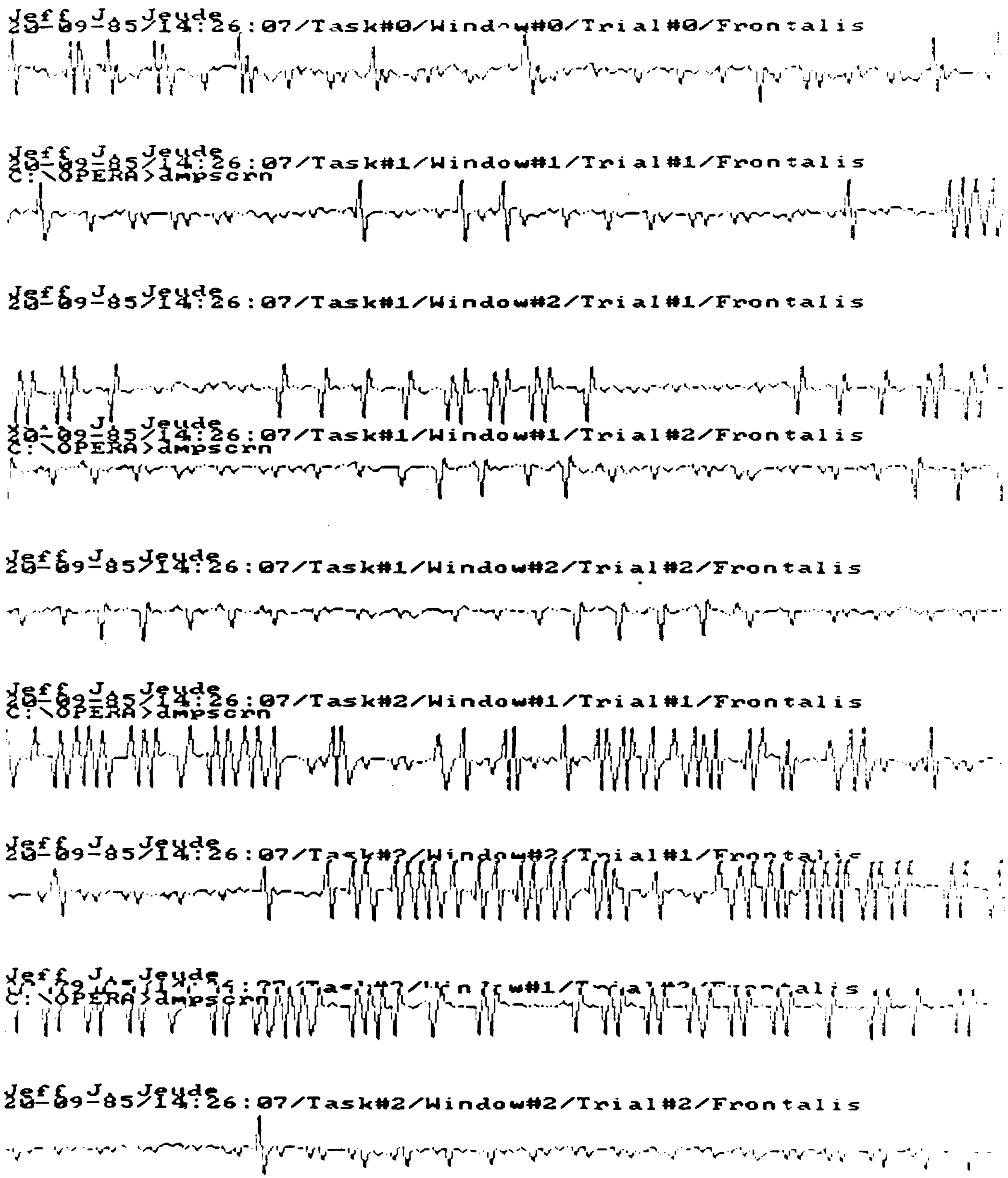
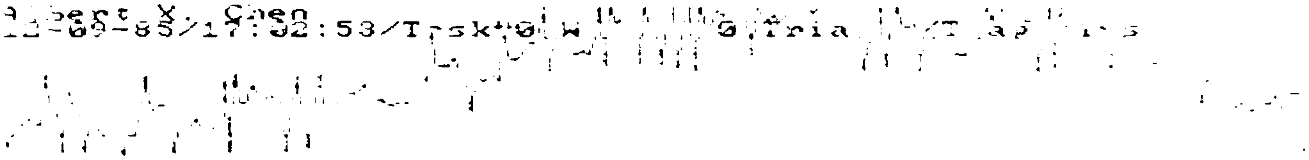
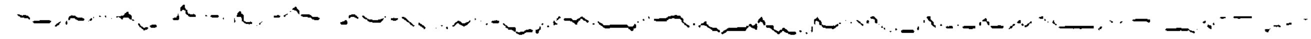


FIGURE 5-3.
MES; SUBJECT: JJJ

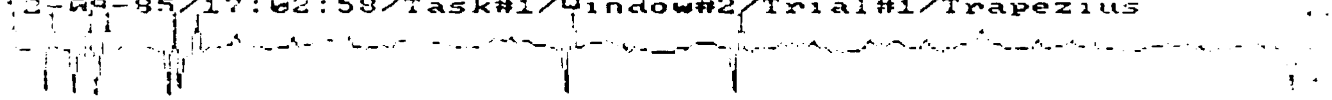
Albert X. Chen
12-09-85/17:02:53/Task#0/W... 0/Tria.../T...ap...



Albert X. Chen
12-09-85/17:02:58/Task#1/Window#1/Trial#1/Trapezius
C:\OPERA>dmpscrn

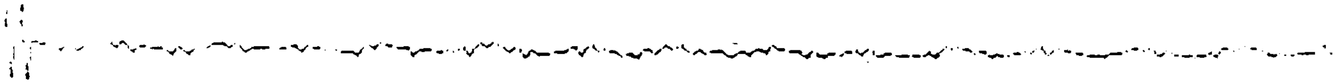


Albert X. Chen
12-09-85/17:02:58/Task#1/Window#2/Trial#1/Trapezius

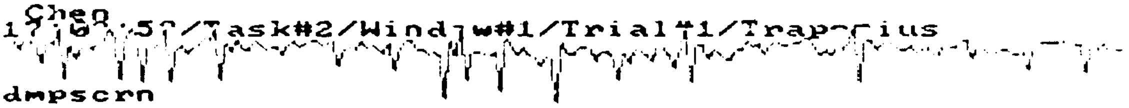


Albert X. Chen
12-09-85/17:02:58/Task#1/Window#1/Trial#2/Trapezius
C:\OPERA>
C:\OPERA>
C:\OPERA>dmpscrn

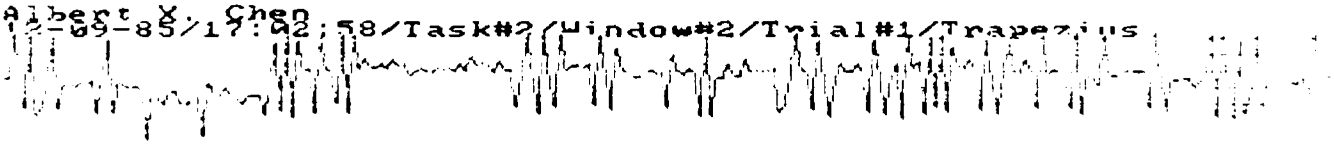
Albert X. Chen
12-09-85/17:02:58/Task#1/Window#2/Trial#2/Trapezius



Albert X. Chen
12-09-85/17:02:58/Task#2/Window#1/Trial#1/Trapezius
C:\OPERA>
C:\OPERA>
C:\OPERA>
C:\OPERA>dmpscrn



Albert X. Chen
12-09-85/17:02:58/Task#2/Window#2/Trial#1/Trapezius



Albert X. Chen
12-09-85/17:02:58/Task#2/Window#1/Trial#2/Trapezius
C:\OPERA>
C:\OPERA>
C:\OPERA>
C:\OPERA>
C:\OPERA>dmpscrn

Albert X. Chen
12-09-85/17:02:58/Task#2/Window#2/Trial#2/Trapezius

6. DISCUSSION OF FINDINGS

Based on the data collected from the Box & Jenkins ARIMA analysis, we were able to compare the MES features between tasks, between trials, between muscle sites and between the rest period and each of the two tasks.

Trends were found in two individuals as a result of careful analysis of the data. Subject JJJ exhibited a definite trend with the frontalis muscle between tasks 1 and 2. Table 6-1 shows the significant pi-weights for this individual with respect to the task, window and trial. A conclusion which can be drawn from this information is that the pi-weights are generally significant for task 2 and not for task 1. Subject AXC exhibited a trend between tasks 1 and 2 also but with the trapezius muscle. Table 6-2 identifies the significant pi-weights with respect to the task, window and trial. Pi-weights for this subject were generally significant in task 1 and not in task 2.

The subjective data indicate a statistically significant difference in perceived stress between the single and dual-task groups. These results are supported by observed differences in performance for 9 of the 12 (or 75% of) the subjects. These performance differences, although in the expected direction, did not reach statistical significance.

The first obvious explanation for the lack of statistical significance between the single and dual-task performance measures is the relatively small number of experimental subjects tested. It is clear that the greater the number of subjects tested, the greater the power of the experimental manipulations, and consequently, the greater the probability that small differences may reach statistically significant levels. Since we knew that a large number of subjects would not be accessible, given the practical constraints under which this study was conducted, we employed a within-

TABLE 6-1

SIGNIFICANT Pi-WEIGHTS (JJJ)

Subject: JJJ (Frontalis)

			Significant P_i-Weights
Task	Window	Trial	5-9
1	1	1	None
1	2	1	None
1	1	2	None
1	2	2	None
2	1	1	5,6
2	2	1	5,6,7,8
2	1	2	None
2	2	2	5

TABLE 6-2

SIGNIFICANT P_i-WEIGHTS (AXC)

Subject: AXC (Trapezius)

			Significant P_i-Weights
Task	Window	Trial	20-25
1	1	1	20,21,22,23
1	2	1	20,22,23,24,25
1	1	2	20,21,22,23
1	2	2	20,21,22,23
2	1	1	20,21,22,23,24,25
2	2	1	20,21,22,23,24,25
2	1	2	None
2	2	2	None

subjects experimental design, which generally provides a more powerful experiment with less subjects than a between-groups design. It is apparent, however, that even under those conditions, the number of subjects tested was inadequate. The fact that three-fourths of the subjects tested did show performance differences between the single and dual-task situations does suggest, however, that using a greater number of subjects may have produced results that were statistically significant.

The experimental tasks used in this study were selected because they are classical tasks. That is, motor tracking and auditory vigilance tasks, in combination, are used throughout the skilled performance literature to "load" the subject and increase task difficulty levels. It is well documented, the time-sharing literature, that imposing a secondary task on a user increases the attentional demands on subjects. In theory, then, the dual-task is more difficult to perform than the single task alone. This has been noted to increase the level of stress under which the subject performs. Because the tasks used were chosen based on their successful use in similar research in the past, the lack of statistical significance of the tracking performance measure in this study requires an alternative explanation.

A more theoretical but certainly plausible explanation for this lack of statistical significance may be advanced based on a cognitive model of allocation of attention (see Kahneman, 1973). While performing the dual-task, the subjects could, in theory, have allocated their attention to the primary tracking task, even though they were instructed that maintaining performance on <u>both</u> primary and secondary tasks was critical. Because the primary (tracking) task was inherently more "entertaining" (more like a video game) and hence perhaps more motivating than the secondary (signal detection task), it is distinctly possible that subjects ignored the instructions and allocated their attention to the primary tracking task. That is, subjects may well have allocated just enough attention to the secondary task of signal detection to perform to their own levels of perceived adequacy, rather than trying to perform well on both tasks. If this was, in fact, the case, then it would be logical that some decrease in primary task performance, and hence observed differences, would be the result, but that those observed differences would not have been profound enough to reach statistical significance. This may also explain why the differences in MES readings associated with the dual-task situation also were not very pronounced.

To determine whether subjects did, in fact, "satisfice" (i.e., perform to their perception of adequacy) in performing the secondary task, one could look at the signal detection performance of subjects in the dual-task situation. Although no "control" group performing signal detection only was employed in this study, one could still expect that if subjects were allocating enough attention to the signal detection task, performance should have been above chance. Stated differently, signal detection performance at or below change levels for the subjects in the dual-task group would indicate that the subjects did not allocate to the secondary task the attention it demanded.

To determine the viability of this explanation, a post-hoc analysis was performed on the raw signal detection data from the subjects in the dual-task situation. The results indicate that all subjects performed below chance levels. On the average, subjects signal detection responses were only correct 13% of the time (see Table 6-3). Three subjects had more incorrect than correct responses (14-18% more incorrect responses), and only two subjects managed to achieve over 40% in correct responses. This may suggest that the subjects performed the dual-task at their level of adequacy by allocating less attention to the secondary task then it called for, and thus, maintaining a consistent level of performance for the primary task.

TABLE 6-3

SECONDARY TASK AVERAGE CORRECT AND INCORRECT RESPONSES FROM TOTAL SIGNALS PRESENTED

SUBJECTS	TRIAL 1	TRIAL 2	AVERAGE
WG	14%	23%	19% (more correct responses)
NI	-10%	-17%	-14% (more incorrect responses)
BN	41%	40%	41.5%
JM	20%	34%	27%
GN	-19%	-16%	-18%
RR	16%	24%	20%
DS	50%	41%	46%
AC	-2%	4%	1%
JJ	-16%	-21%	-19%
FH	-37%	-19%	-28%
DN	33%	31%	32%
JF	12%	18%	15%

Summary: On the average, subjects achieved 13% more correct responses than incorrect responses (see Section 6.0 for a discussion)

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APPENDIX A

SOFTWARE SPECIFICATIONS

Appendix A

Software Specifications

Overview

The two software packages involved in the myoelectric signal acquisition consist of one system for the IBM XT and one for the Apple IIe. The IBM XT is used to control the newly acquired data acquisition system, the experimental parameters and the Apple IIe. The Apple IIe is used to present the tasks to the subjects, to record subject responses and to print a subject performance record.

Apple IIe System

There are two tasks present on the Apple IIe which are both written in Apple GraForth. When not performing either task or printing out a performance record, the Apple waits for a task number to be received from the IBM.

Task 1 is a straightforward tracking task. This task consists of a crosshair which moves randomly at a constant rate about the screen along both x and y axes. The subject has joystick control over a circle on the screen. The object is to keep the crosshair as close to the center of the circle as possible for the 3.5 minutes duration of the task.

Task 2 consists of task 1 along with a simultaneous auditory task. At random intervals, a short tone is emitted from the Apple's speaker. Sixth per cent of the time, this tone will be high pitched. At this point the subject has exactly 0.5 seconds to respond to the tone by pressing the joystick button. The system then responds with a much higher tone to acknowledge the button press. Forty per cent of the time however, the tone will be low pitched. Should the subject respond to this lower tone, it is recorded as an error.

A restriction is placed on the high tones. Once a high tone is emitted there will not be another high tone for at least 0.5 seconds. Nevertheless, any number of low tones can be sounded within this period. This is done to allow the subject time to respond to the tone.

Also, once the joystick button is pressed, it is not polled again for the next 0.5 second. This is done in order to remove the possibility of a double press for a given tone.

Recording of Performance

In both tasks, a running average of the distance from the center of the circle to the center of the crosshair is calculated. Every ten seconds this is stored in a buffer and the average distance is reset to zero.

In task 2, responses to the tones are also recorded. These are grouped into three categories: good responses, false responses and no responses. A good response occurs when the joystick button is pressed within 0.5 seconds after a high tone is emitted. A false response is recorded when the joystick button is pressed but there was no high tone emitted within the previous 0.5 seconds. Finally, a no response occurs when 0.5 seconds passes after a high tone is emitted without the joystick button being pressed. As with the average distance, every ten seconds, the tone responses are stored in a buffer and reset to zero.

Upon terminating the task, the Apple prints its response buffers and returns to its initial waiting state.

IBM XT System

The system on the IBM XT is completely written in C and consists of four primary functions.

- o Control the Apple IIe.
- o Interface with the data acquisition system.
- o Plot the data files received from the data acquisition system.
- o Interface with the experimenter.

Control of the Apple IIe

The IBM communicates with the Apple IIe over an RS-232 line to inform it to start a particular task and to find out when this task is finished. When the IBM system wants to start a particular task, it sends the desired task number (1 or 2) to the Apple. The Apple, upon receiving this number, prompts the subject for his name and instructs the subject to press the joystick button when he is ready. The Apple then returns the task number to the IBM to indicate the start of the task. Once the task is finished, the task number is once again sent to the IBM to indicate this fact.

Interface with the Data Acquisition System

The IBM communicates with the MDAS 7000 data acquisition system over an IEEE-488 (GPIB) bus to set up the sampling parameters, to inform the MDAS 7000 to sample data and to download files to the IBM.

The only sampling parameters involved are the sampling rate, the sampling duration and the channel selection. The MDAS 7000 is instructed by the IBM to sample two channels specified for the frontalis and trapezius muscle sites for one second at a rate of 1000 samples per second.

Once, at the beginning of the experiment and at exactly 2.75 and at 3.25 minutes into each task, the MDAS 7000 is instructed to sample the two channels and to send the two files to the IBM for storage.

File Format Convention

The data files consist of a 100 character descriptive header followed by 1000 integers in ASCII format. The descriptive header is in the following format:

Name/Data/Time/Task#__/Window#__/Trial#__/Muscle Site

The blanks are filled in with the appropriate values. The windows are numbered as follows:

0 - At rest
1 - 2.75 minutes into the task
2 - 3.25 minutes into the task

The name of each file begins with the three initials of the subject, where the letter "X" is used if the subject has no middle name. This is followed by a letter representing the muscle site: 'a' for frontalis, 'c' for trapezius. If the file represents a sample at rest then the string 'atrest' is appended to the filename. Otherwise, the task number, the window number and the trial number are appended to the filename in that order along with a '.dat' suffix.

Plot the Data Files

The data plotting package on the IBM is further explained in section 3.5. Whenever the IBM receives a set of two data files from the MDAS 7000, it plots the first 300 points of each file simultaneously with a horizontal magnification of 2 and a vertical reduction of 31. This remains on the screen until a new set data is received, or a new task begins.

Interface with Experimenter

When the program, 'OPERA', is executed on the IBM, the screen clears and the system prompts for the subject's name. Once a valid name with three initials is typed, the subject is sampled at rest, and the two files are plotted and stored and the following appears:

    Practice first? (y/n)

Should the experimenter wish the subject to go through a practice round before any data is taken, the experimenter responds with 'y'. Otherwise, the actual experiment will begin.

If, however, a practice round is desired, the following prompt appears:

    Practice task #

Valid responses to this are a '1' and a '2'. Any other responses will be rejected. The task number is then send to the Apple IIe which then presents the appropriate task to the subject. Once the subject has entered his name and pressed the joystick button, the task number is sent back to the IBM. The IBM acknowledges with:

    Task # __started

where the blank is filled in with the appropriate task number. The IBM then sits in a waiting state until the task number is once again received from the Apple indicating that the task has terminated. Upon receiving the character, the IBM types:

    Continue practice? (y/n)

at which point it will repeat the entire practice sequence if the response is affirmative. Otherwise, the actual experiment begins and the following appears:

    Trial #

The experimenter replies with either a '1' or a '2'. The system responds with:

    Task (1,2)

The experimenter replies with either a '1' or a '2' depending on the task difficulty desired. The task number is then send to the Apple and the IBM types:

    Waiting for task to start on Apple IIe...

Upon receiving the task number from the Apple, indicating the start of the task, a timer is started and the following appears:

    Task # __started

where the blank is filled in with the appropriate task number.

At exactly 2.75 and 3.25 minutes into the task, the data acquisition system receives a message from the IBM to sample the two channels specified for the frontalis and trapezius muscles for one second at a rate of 1000 samples per second. The acquired data is immediately sent to the IBM. Once received, the two sets of data are plotted simultaneously for the experimenter to check the signal integrity.

When the task is terminated, the Apple indicates this, as in the practice session, by sending the task number to the IBM. The IBM acknowledges this by typing:

Continue? (y/n)

If the response is affirmative the entire process after the practice session is repeated. Otherwise the program terminates.

APPENDIX B

INSTRUCTIONS FOR EXPERIMENTAL SUBJECTS

APPENDIX B

INSTRUCTIONS FOR EXPERIMENTAL SUBJECTS

This experiment is part of a program of continuing research at Perceptronics in human (pilot) performance and decision making. The purpose of this particular experiment is to analyze ways in which human operators' myoelectric (muscle) signals respond and how a computer might help to determine an operator's mental state via these signals. You are an integral part of this research since your performance provides the baseline data for predicting operator performance, and estimating the effectiveness of computer-based analysis techniques.

Tasks Overview

There are two types of tasks that you will be asked to perform in the experiment. They are: (1) motor (control) tracking task, and (2) motor plus perceptual (control + auditory) task. Each task will be approximately 3-1/2 minutes each. Please concentrate on the task, as your responses and performance will be closely monitored and scored. There will be a predetermined pay-scale for performance levels, thus the better you do, the more money you will make. At the end of each session, you will be given a questionnaire to fill out. Information on these questionnaires will not be used to rate your score, so please use your unbiased judgment to answer those questions.

The following paragraphs describe the two types of tasks.

Motor (Control) Tracking Task. In this task, you will see an object called the "target" which moves freely around the screen. You will be asked to track the target by controlling another object, called the "site" with a joystick. The objective is to track and surround the target with the site as the target continually moves around the screen. Performance will be measured as the average distance between the site and target over the entire task.

Motor + Perceptrual (Control + Auditory) Task. This task incorporates the first motor tracking task with a perceptual, auditory task. In addition to the first motor tracking task, you will be required to respond to high tones by pressing the orange button on the top of the joystick whenever a high tone is heard. There will be low tones and high tones--you must discriminate between the two tones and only respond to the high tones. Overall performance will be measured as (1) average distance between the site and target and (2) good responses, false responses and missed responses to the high tones.

APPENDIX C

EXPERIMENTAL SUBJECT QUESTIONNAIRE

OPERA
QUESTIONNAIRE

Name ____________________ Date ____________________

Sex ____________

Age ____________

Please answer the following questions truthfully and as accurately as possible by placing an 'X' on the line below the question

If, for some questions you feel you need more information to base your answer on, then you may just guess

1 How simple was the task?

|____|

extremely simple — extremely complicated

2 What level of effort did you expend?

|____|

very low — very high

3 How much did you enjoy the session?

|____|

not at all — extremely

4 How challenging was the session?

|____|

not at all — extremely

5 What do you think your score was for this task?

very low — very high

6 How much attention did you put forth for this task?

very low — very high

7 How exciting was the task?

not at all — extremely

8 How much strain did you experience during the session?

none — very much

General observations and comments.

APPENDIX D

SAMPLE PRINTOUT AND ANALYSIS
WITH PERFORMANCE MEASURE PRINTOUT

PERFORMANCE MEASURE PRINTOUT

SUBJECT: MICKEY ODEGAARD

LEVEL	AVERAGE DISTANCE
1	2
1	2
1	2
2	11
2	5
3	11
3	12
3	14
4	19
4	22
4	23
5	27
5	47
5	28
6	36
6	33
6	34
7	32
7	56
7	52

PERFORMANCE MEASURE PRINTOUT

SUBJECT: JAY MARTIN

LEVEL	AVERAGE DISTANCE	GOOD RESPONSE	NO RESPONSE	FALSE RESPONSE
1	21	0	3	3
1	31	2	0	0
1	20	1	0	0
2	20	2	2	2
2	15	3	1	0
2	17	1	2	2
3	17	5	2	2
3	15	7	2	2
3	19	8	0	0
4	19	9	2	2
4	22	6	0	0
4	12	11	2	2
5	19	8	0	0
5	21	7	3	2
5	21	3	0	2

Appendix D (Cont'd)

AUTOBJ SAMPLE PRINTOUT (SUBJECT: AXC)

```
==============================================================================
MODELING RESULTS FOR TIME SERIES AXCAATRE
==============================================================================

      ****************************************************************
      DATA :    Z = AXCAATRE  10000.                     1000 OBSERVATIONS

      DIFFERENCING ON   Z : NONE

      BACKCASTING : OFF
      ****************************************************************
      UNIVARIATE MODEL PARAMETERS
      ****************************************************************
                      FACTOR   LAG COEFFICIENT        T RATIO

      ****************************************************************
       1 MEAN                     -.12557E+01
       2 AUTOREGRESSIVE 1      2   .17341E+00          4.94
       3 AUTOREGRESSIVE 1      3   .20123E+00          6.20
       4 AUTOREGRESSIVE 2     10   .47839E+00         16.06
       5 AUTOREGRESSIVE 2     30   .23716E+00          7.99
       6 MOVING AVERAGE 1      1   .48090E+00         14.64
       7 MOVING AVERAGE 2     70  -.14074E+00         -4.32
      ****************************************************************

                         THE RESIDUAL STATISTICS
                         =======================

   SUM OF SQUARES :  .41084E-01          DEGREES OF FREEDOM   :      960
   MEAN SQUARE    :  .42796E-04          NUMBER OF RESIDUALS  :      967
   R SQUARED      :  .51239E+00



                              THE PI WEIGHTS
                              ==============


UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST
PLUS A RANDOM SHOCK.  DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE
TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO  OTHER TYPES OF MODELS.


      THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

  Z(t)   =  Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)
```

LAG	THE PI WEIGHT
Constant	-.38640E+01
Pi(1)	-.48090E+00
Pi(2)	-.40467E+00
Pi(3)	-.39584E+00
Pi(4)	-.19036E+00
Pi(5)	-.91543E-01
Pi(6)	-.44023E-01
Pi(7)	-.21170E-01
Pi(8)	-.10181E-01
Pi(10)	-.48075E+00
Pi(11)	-.23119E+00
Pi(12)	-.28221E-01
Pi(13)	.82697E-01
Pi(14)	.39769E-01
Pi(15)	.19125E-01
Pi(30)	-.23716E+00
Pi(31)	-.11405E+00
Pi(32)	-.13720E-01
Pi(33)	.41127E-01
Pi(34)	.19778E-01
Pi(70)	.14074E+00
Pi(71)	.67684E-01
Pi(72)	.56956E-01
Pi(73)	.55712E-01
Pi(74)	.26792E-01
Pi(75)	.12884E-01
Pi(80)	.67663E-01
Pi(81)	.32539E-01
Pi(83)	-.11639E-01
Pi(100)	.33380E-01
Pi(101)	.16052E-01
Pi(140)	-.19809E-01

MODELING RESULTS FOR TIME SERIES AXCCATRE

DATA : Z = AXCCATRE 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.18902E+01	
2 AUTOREGRESSIVE	1	1	.17256E+00	5.34
3 AUTOREGRESSIVE	1	2	.56137E+00	10.83
4 AUTOREGRESSIVE	1	3	.17522E+00	4.24
5 AUTOREGRESSIVE	2	30	.11582E+00	3.57
6 MOVING AVERAGE	1	2	.27510E+00	4.40
7 MOVING AVERAGE	2	50	-.17444E+00	-5.24

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.12558E+00	DEGREES OF FREEDOM :	960
MEAN SQUARE :	.13081E-03	NUMBER OF RESIDUALS :	967
R SQUARED :	.62287E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.42620E+01
Pi(1)	-.17256E+00
Pi(2)	-.83646E+00
Pi(3)	-.22269E+00
Pi(4)	-.23011E+00
Pi(5)	-.61261E-01
Pi(6)	-.63302E-01
Pi(7)	-.16853E-01
Pi(8)	-.17414E-01
Pi(30)	-.11582E+00
Pi(31)	.19986E-01
Pi(32)	.33157E-01
Pi(33)	.25793E-01
Pi(50)	.17444E+00
Pi(51)	.30101E-01
Pi(52)	.14592E+00
Pi(53)	.38847E-01
Pi(54)	.40141E-01
Pi(55)	.10687E-01
Pi(56)	.11043E-01
Pi(80)	.20205E-01
Pi(100)	-.30431E-01
Pi(102)	-.25454E-01

MODELING RESULTS FOR TIME SERIES AXCA111.

```
DATA :    Z = AXCA111.    1000.                    1000 OBSERVATIONS

DIFFERENCING ON    Z : NONE

BACKCASTING : OFF
```

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1	MEAN		-.27796E+01	
2	AUTOREGRESSIVE 1	20	.11212E+00	3.50
3	MOVING AVERAGE 1	1	.34025E+00	11.32
4	MOVING AVERAGE 1	3	-.91043E-01	-3.00
5	MOVING AVERAGE 2	40	-.13533E+00	-4.21

THE RESIDUAL STATISTICS

```
SUM OF SQUARES :  .27911E+01          DEGREES OF FREEDOM   :    975
MEAN SQUARE    :  .28626E-02          NUMBER OF RESIDUALS  :    980
R SQUARED      :  .12517E+00
```

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.36265E+01
Pi(1)	-.34025E+00
Pi(2)	-.11577E+00
Pi(3)	.51652E-01
Pi(4)	.48552E-01
Pi(5)	.27060E-01
Pi(20)	-.11212E+00
Pi(21)	-.38148E-01
Pi(22)	-.12980E-01
Pi(40)	.13533E+00
Pi(41)	.46046E-01
Pi(42)	.15667E-01
Pi(60)	.15173E-01
Pi(80)	-.18314E-01

MODELING RESULTS FOR TIME SERIES AXCC111.

DATA : Z = AXCC111. 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.19609E+01	
2 AUTOREGRESSIVE	1	1	.27079E+00	8.62
3 AUTOREGRESSIVE	1	2	.34385E+00	11.27
4 AUTOREGRESSIVE	1	3	.19783E+00	6.35
5 MOVING AVERAGE	1	20	-.18812E+00	-5.81

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.87317E-02	DEGREES OF FREEDOM :	992
MEAN SQUARE :	.88021E-05	NUMBER OF RESIDUALS :	997
R SQUARED :	.56219E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.29914E+01
Pi(1)	-.27073E+00
Pi(2)	-.34385E+00
Pi(3)	-.19783E+00
Pi(20)	.18812E+00
Pi(21)	.50940E-01
Pi(22)	.64683E-01
Pi(23)	.37214E-01
Pi(40)	-.35388E-01
Pi(42)	-.12168E-01

==

MODELING RESULTS FOR TIME SERIES AXCA121.

==

DATA : Z = AXCA121. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.28824E+01	
2 AUTOREGRESSIVE	1	10	.20174E+00	6.27
3 MOVING AVERAGE	1	1	.27375E+00	8.65
4 MOVING AVERAGE	1	2	-.12206E+00	-3.85
5 MOVING AVERAGE	2	40	-.89747E-01	-2.72

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.14656E+01	DEGREES OF FREEDOM :	985
MEAN SQUARE :	.14880E-02	NUMBER OF RESIDUALS :	990
R SQUARED :	.11139E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.37470E+01
Pi(1)	-.27375E+00
Pi(2)	.47121E-01
Pi(3)	.46313E-01
Pi(10)	-.20176E+00
Pi(11)	-.55233E-01
Pi(40)	.89747E-01
Pi(41)	.24568E-01
Pi(50)	.18105E-01

MODELING RESULTS FOR TIME SERIES AXCC121.

DATA : Z = AXCC121. 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.19481E+01	
2 AUTOREGRESSIVE	1	2	.65102E+00	9.57
3 AUTOREGRESSIVE	1	3	.20268E+00	7.40
4 MOVING AVERAGE	1	1	.23592E+00	7.46
5 MOVING AVERAGE	1	2	.52311E+00	6.72
6 MOVING AVERAGE	2	20	-.20041E+00	-6.15

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.75131E-01	DEGREES OF FREEDOM :	991
MEAN SQUARE :	.75813E-04	NUMBER OF RESIDUALS :	997
R SQUARED :	.11171E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.12484E+02
Pi(1)	-.23592E+00
Pi(2)	-.12298E+01
Pi(3)	-.61621E+00
Pi(4)	-.78870E+00
Pi(5)	-.50842E+00
Pi(6)	-.53252E+00
Pi(7)	-.39159E+00
Pi(8)	-.37095E+00
Pi(9)	-.29236E+00
Pi(10)	-.26302E+00
Pi(11)	-.21499E+00
Pi(12)	-.18831E+00
Pi(13)	-.15689E+00
Pi(14)	-.13552E+00
Pi(15)	-.11404E+00
Pi(16)	-.97797E-01
Pi(17)	-.82729E-01
Pi(18)	-.70676E-01
Pi(19)	-.59951E-01
Pi(20)	.14930E+00
Pi(22)	.20948E+00
Pi(23)	.92058E-01
Pi(24)	.13130E+00
Pi(25)	.79132E-01
Pi(26)	.87354E-01
Pi(27)	.62003E-01
Pi(28)	.60324E-01
Pi(29)	.46666E-01
Pi(30)	.42565E-01
Pi(31)	.34454E-01
Pi(32)	.30395E-01
Pi(33)	.25194E-01
Pi(34)	.21844E-01
Pi(35)	.18332E-01
Pi(36)	.15752E-01
Pi(37)	.13306E-01
Pi(38)	.11379E-01
Pi(40)	-.31936E-01
Pi(42)	-.43441E-01
Pi(43)	-.19691E-01
Pi(44)	-.27370E-01
Pi(45)	-.16758E-01
Pi(46)	-.18271E-01
Pi(47)	-.13077E-01
Pi(48)	-.12643E-01

MODELING RESULTS FOR TIME SERIES AXCA211.

DATA : Z = AXCA211. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.33753E+01	
2 AUTOREGRESSIVE	1	1	-.54606E+00	-17.36
3 AUTOREGRESSIVE	1	2	-.24740E+00	-7.86
4 AUTOREGRESSIVE	2	10	.14738E+00	4.60
5 AUTOREGRESSIVE	2	20	.16534E+00	5.27
6 MOVING AVERAGE	1	30	-.24072E+00	-7.34

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.32738E+01	DEGREES OF FREEDOM :	973
MEAN SQUARE :	.33681E-02	NUMBER OF RESIDUALS :	978
R SQUARED :	.34592E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.20877E+01
Pi(1)	.54606E+00
Pi(2)	.24740E+00
Pi(10)	-.14738E+00
Pi(11)	-.80478E-01
Pi(12)	-.36461E-01
Pi(20)	-.16534E+00
Pi(21)	-.90286E-01
Pi(22)	-.40905E-01
Pi(30)	.24072E+00
Pi(31)	-.13145E+00
Pi(32)	-.59553E-01
Pi(40)	.35477E-01
Pi(41)	.19373E-01
Pi(50)	.39801E-01
Pi(51)	.21734E-01
Pi(60)	-.57947E-01
Pi(61)	.31642E-01
Pi(62)	.14336E-01
Pi(90)	.13949E-01

==

MODELING RESULTS FOR TIME SERIES AXCC211.

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DATA :   Z = AXCC211.   10000.   1000 OBSERVATIONS

DIFFERENCING ON   Z : NONE

BACKCASTING : OFF

****

UNIVARIATE MODEL PARAMETERS

****

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.15278E+01	
2 AUTOREGRESSIVE	1	2	.69118E+00	17.91
3 AUTOREGRESSIVE	1	3	.25295E+00	9.24
4 AUTOREGRESSIVE	2	10	.32810E+00	10.69
5 MOVING AVERAGE	1	1	.21918E+00	6.89
6 MOVING AVERAGE	1	2	.62209E+00	13.34
7 MOVING AVERAGE	2	60	.14956E+00	4.52

****

THE RESIDUAL STATISTICS

=====================

SUM OF SQUARES :	.47244E-01	DEGREES OF FREEDOM :	990
MEAN SQUARE :	.48208E-04	NUMBER OF RESIDUALS :	997
R SQUARED :	.22098E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.22211E+02
Pi(1)	-.21918E+00
Pi(2)	-.13613E+01
Pi(3)	-.68766E+00
Pi(4)	-.99758E+00
Pi(5)	-.64644E+00
Pi(6)	-.76227E+00
Pi(7)	-.56922E+00
Pi(8)	-.59897E+00
Pi(9)	-.48539E+00
Pi(10)	-.80710E+00
Pi(11)	-.47885E+00
Pi(12)	-.38027E+00
Pi(13)	-.29825E+00
Pi(14)	-.30193E+00
Pi(15)	-.25171E+00
Pi(16)	-.24300E+00
Pi(17)	-.20985E+00
Pi(18)	-.19716E+00
Pi(19)	-.17376E+00
Pi(20)	-.16074E+00
Pi(21)	-.14332E+00
Pi(22)	-.13141E+00
Pi(23)	-.11796E+00
Pi(24)	-.10760E+00
Pi(25)	-.96968E-01
Pi(26)	-.88192E-01
Pi(27)	-.79653E-01
Pi(28)	-.72322E-01
Pi(29)	-.65403E-01
Pi(30)	-.59326E-01
Pi(31)	-.53690E-01
Pi(32)	-.48674E-01
Pi(33)	-.44068E-01
Pi(34)	-.39938E-01
Pi(35)	-.36168E-01
Pi(36)	-.32773E-01
Pi(37)	-.29683E-01
Pi(38)	-.26893E-01
Pi(39)	-.24360E-01
Pi(40)	-.22069E-01

Pi(41)	-.19991E-01
Pi(42)	-.18111E-01
Pi(43)	-.16406E-01
Pi(44)	-.14862E-01
Pi(45)	-.13464E-01
Pi(46)	-.12197E-01
Pi(47)	-.11049E-01
Pi(48)	-.10009E-01
Pi(60)	-.15262E+00
Pi(61)	-.35550E-01
Pi(62)	-.20611E+00
Pi(63)	-.10512E+00
Pi(64)	-.15126E+00
Pi(65)	-.98549E-01
Pi(66)	-.11570E+00
Pi(67)	-.86665E-01
Pi(68)	-.90970E-01
Pi(69)	-.73852E-01
Pi(70)	-.12185E+00
Pi(71)	-.72650E-01
Pi(72)	-.57808E-01
Pi(73)	-.45453E-01
Pi(74)	-.45924E-01
Pi(75)	-.38341E-01
Pi(76)	-.36973E-01
Pi(77)	-.31956E-01
Pi(78)	-.30004E-01
Pi(79)	-.26456E-01
Pi(80)	-.24464E-01
Pi(81)	-.21820E-01
Pi(82)	-.20001E-01
Pi(83)	-.17958E-01
Pi(84)	-.16379E-01
Pi(85)	-.14761E-01
Pi(86)	-.13424E-01
Pi(87)	-.12125E-01
Pi(88)	-.11009E-01
Pi(120)	-.22835E-01
Pi(122)	-.30833E-01
Pi(123)	-.15729E-01
Pi(124)	-.22629E-01
Pi(125)	-.14744E-01
Pi(126)	-.17309E-01
Pi(127)	-.12966E-01
Pi(128)	-.13610E-01
Pi(129)	-.11049E-01
Pi(130)	-.18227E-01
Pi(131)	-.10869E-01

MODELING RESULTS FOR TIME SERIES AXCA221.

DATA : Z = AXCA221. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

		FACTOR	LAG	COEFFICIENT	T RATIO
1	MEAN			-.33928E+01	
2	AUTOREGRESSIVE	1	1	-.30822E+00	-10.06
3	AUTOREGRESSIVE	1	3	.15107E+00	4.76
4	AUTOREGRESSIVE	1	4	.13222E+00	4.15
5	AUTOREGRESSIVE	2	10	.34040E+00	10.75
6	AUTOREGRESSIVE	2	20	.20789E+00	6.38
7	MOVING AVERAGE	1	40	-.16729E+00	-4.86

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.29161E+01	DEGREES OF FREEDOM :	969
MEAN SQUARE :	.30094E-02	NUMBER OF RESIDUALS :	976
R SQUARED :	.35080E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.44675E+01
Pi(1)	.30822E+00
Pi(3)	-.15107E+00
Pi(4)	-.13222E+00
Pi(10)	-.34040E+00
Pi(11)	-.10492E+00
Pi(13)	.51426E-01
Pi(14)	.45007E-01
Pi(20)	-.20789E+00
Pi(21)	-.64076E-01
Pi(23)	.31407E-01
Pi(24)	.27487E-01
Pi(40)	.16729E+00
Pi(41)	-.51561E-01
Pi(43)	.25273E-01
Pi(44)	.22118E-01
Pi(50)	.56946E-01
Pi(51)	.17552E-01
Pi(60)	.34778E-01
Pi(61)	.10719E-01
Pi(80)	-.27986E-01

MODELING RESULTS FOR TIME SERIES AXCC221.

DATA : Z = AXCC221. 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1	MEAN		-.14343E+01	
2	AUTOREGRESSIVE 1	10	.28348E+00	8.96
3	MOVING AVERAGE 1	1	.39625E+00	13.68
4	MOVING AVERAGE 1	3	-.21290E+00	-7.32
5	MOVING AVERAGE 2	20	-.15849E+00	-4.77

THE RESIDUAL STATISTICS

SUM OF SQUARES : .13406E+00
MEAN SQUARE : .13610E-03
R SQUARED : .22719E+00

DEGREES OF FREEDOM : 985
NUMBER OF RESIDUALS : 990

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

$$Z(t) = \text{Constant} + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) \ldots + Pi(n) * Z(t-n)$$

LAG	THE PI WEIGHT
Constant	-.19458E+01
Pi(1)	-.39625E+00
Pi(2)	-.15702E+00
Pi(3)	.15068E+00
Pi(4)	.14407E+00
Pi(5)	.90516E-01
Pi(7)	-.29171E-01
Pi(8)	-.30830E-01
Pi(9)	-.13023E-01
Pi(10)	-.28243E+00
Pi(11)	-.10535E+00
Pi(12)	-.38973E-01
Pi(13)	.44686E-01
Pi(14)	.40136E-01
Pi(15)	.24201E-01
Pi(20)	.15897E+00
Pi(21)	.64809E-01
Pi(22)	.26401E-01
Pi(23)	-.23382E-01
Pi(24)	-.23063E-01
Pi(25)	-.14759E-01
Pi(30)	.44807E-01
Pi(31)	.16701E-01
Pi(40)	-.25194E-01
Pi(41)	-.10272E-01

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=================================================================================
MODELING RESULTS FOR TIME SERIES AXCA1.2.
=================================================================================

     ****************************************************************
     DATA :    Z = AXCA112.    1000.                  1000 OBSERVATIONS

     DIFFERENCING ON    Z : NONE

     BACKCASTING : OFF
     ****************************************************************
     UNIVARIATE MODEL PARAMETERS
     ****************************************************************
                   FACTOR   LAG COEFFICIENT        T RATIO

     ****************************************************************
      1 MEAN                    -.21328E+01
      2 AUTOREGRESSIVE 1     1  -.20114E+00         -6.28
      3 AUTOREGRESSIVE 1     2   .11076E+00          3.41
      4 AUTOREGRESSIVE 1     3   .15122E+00          4.72
      5 AUTOREGRESSIVE 2    10   .29527E+00          9.63
      6 AUTOREGRESSIVE 2    30   .19493E+00          6.24
      7 MOVING AVERAGE 1    40  -.84168E-01         -2.49
     ****************************************************************

                          THE RESIDUAL STATISTICS
                          =======================

   SUM OF SQUARES :  .11558E+01        DEGREES OF FREEDOM  :      960
   MEAN SQUARE    :  .12040E-02        NUMBER OF RESIDUALS :      967
   R SQUARED      :  .22893E+00



                              THE PI WEIGHTS
                              ==============

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST
PLUS A RANDOM SHOCK.  DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE
TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO  OTHER TYPES OF MODELS.

      THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

  Z(t)  =  Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n
```

LAG	THE PI WEIGHT
Constant	-.29926E+01
Pi(1)	.20114E+00
Pi(2)	-.11076E+00
Pi(3)	-.15122E+00
Pi(10)	-.29527E+00
Pi(11)	-.59392E-01
Pi(12)	.32705E-01
Pi(13)	.44652E-01
Pi(30)	-.19493E+00
Pi(31)	-.39208E-01
Pi(32)	.21590E-01
Pi(33)	.29477E-01
Pi(40)	.84168E-01
Pi(41)	-.16930E-01
Pi(43)	.12728E-01
Pi(50)	.24852E-01
Pi(70)	.16407E-01

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MODELING RESULTS FOR TIME SERIES AXCC112.

==

DATA : Z = AXCC112. 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1	MEAN		-.11113E+01	
2	AUTOREGRESSIVE 1	1	.65572E-01	2.10
3	AUTOREGRESSIVE 1	2	.43537E+00	.5.80
4	AUTOREGRESSIVE 1	3	.26764E+00	8.63
5	AUTOREGRESSIVE 2	10	.17803E+00	5.55
6	MOVING AVERAGE 1	20	-.27222E+00	-8.51

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.53127E-02	DEGREES OF FREEDOM :	981
MEAN SQUARE :	.54156E-05	NUMBER OF RESIDUALS :	987
R SQUARED :	.51480E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

$$Z(t) = \text{Constant} + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) \ldots + Pi(n) * Z(t-n)$$

LAG	THE PI WEIGHT
Constant	-.15809E+01
Pi(1)	-.65572E-01
Pi(2)	-.43537E+00
Pi(3)	-.26764E+00
Pi(10)	-.17803E+00
Pi(11)	.11674E-01
Pi(12)	.77509E-01
Pi(13)	.47648E-01
Pi(20)	.27222E+00
Pi(21)	.17850E-01
Pi(22)	.11852E+00
Pi(23)	.72858E-01
Pi(30)	.48464E-01
Pi(32)	-.21100E-01
Pi(33)	-.12971E-01
Pi(40)	-.74106E-01
Pi(42)	-.32263E-01
Pi(43)	-.19834E-01
Pi(50)	-.13193E-01
Pi(60)	.20173E-01

MODELING RESULTS FOR TIME SERIES AXCA122.

DATA : Z = AXCA122. 1000. 1000 OBSERVATIONS

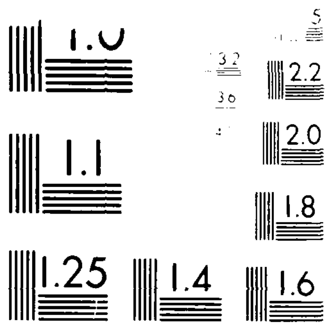
DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.20727E+01	
2 AUTOREGRESSIVE	1	10	.41588E+00	13.87
3 AUTOREGRESSIVE	1	30	.28056E+00	9.53
4 MOVING AVERAGE	1	1	.53277E+00	18.84
5 MOVING AVERAGE	1	3	-.12710E+00	-4.43
6 MOVING AVERAGE	2	20	-.18495E+00	-5.49

AD-A168 567 OPERATOR ALERTNESS/WORKLOAD ASSESSMENT USING STOCHASTIC 2/2
MODEL-BASED ANALY..(U) PERCEPTRONICS INCWOODLAND HILLS
CA A MADNI ET AL. NOV 85 PFTR-1126-85-11
UNCLASSIFIED AFOSR-TR-86-0325 F49620-83-C-0001 F/G 5/9 NL


2.2
2.0
1.1
1.8
1.25
1.4
1.6

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.51580E+01	DEGREES OF FREEDOM :	964
MEAN SQUARE :	.53506E-02	NUMBER OF RESIDUALS :	970
R SQUARED :	.52418E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.49928E+01
Pi(1)	-.53277E+00
Pi(2)	-.28384E+00
Pi(3)	-.24120E-01
Pi(4)	.54864E-01
Pi(5)	.65306E-01
Pi(6)	.37858E-01
Pi(7)	.13196E-01
Pi(10)	-.42048E+00
Pi(11)	-.22386E+00
Pi(12)	-.11857E+00
Pi(14)	.23271E-01
Pi(15)	.27468E-01
Pi(16)	.15870E-01
Pi(20)	.18301E+00
Pi(21)	.97574E-01
Pi(22)	.52279E-01
Pi(25)	-.11949E-01
Pi(30)	-.20281E+00
Pi(31)	-.10808E+00
Pi(32)	-.57706E-01
Pi(34)	.11090E-01
Pi(35)	.13243E-01
Pi(40)	-.35138E-01
Pi(41)	-.18688E-01
Pi(50)	.37517E-01
Pi(51)	.19988E-01
Pi(52)	.10670E-01

MODELING RESULTS FOR TIME SERIES AXCC122.

DATA : Z = AXCC122. 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.10951E+01	
2 AUTOREGRESSIVE	1	1	.19957E+00	4.07
3 AUTOREGRESSIVE	1	2	.10598E+00	2.39
4 AUTOREGRESSIVE	1	3	.48950E+00	17.09
5 MOVING AVERAGE	1	1	.17681E+00	3.04
6 MOVING AVERAGE	1	2	-.10757E-01	-.20
7 MOVING AVERAGE	2	20	-.22387E+00	-7.00

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.88485E-02	DEGREES OF FREEDOM :	990
MEAN SQUARE :	.89379E-05	NUMBER OF RESIDUALS :	997
R SQUARED :	.41752E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.19261E+01
Pi(1)	-.37638E+00
Pi(2)	-.16177E+00
Pi(3)	-.51405E+00
Pi(4)	-.89148E-01
Pi(5)	-.10232E-01
Pi(20)	.22387E+00
Pi(21)	.84259E-01
Pi(22)	.36215E-01
Pi(23)	.11508E+00
Pi(24)	.19957E-01
Pi(40)	-.50116E-01
Pi(41)	-.18863E-01
Pi(43)	-.25762E-01
Pi(60)	.11219E-01

MODELING RESULTS FOR TIME SERIES AXCA212.

DATA : Z = AXCA212. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.19370E+01	
2 AUTOREGRESSIVE	1	1	.47668E+00	1.52
3 AUTOREGRESSIVE	1	2	.35548E+00	1.40
4 AUTOREGRESSIVE	1	3	.13653E+00	2.12
5 AUTOREGRESSIVE	2	10	.19872E+00	6.18
6 MOVING AVERAGE	1	1	.53595E+00	1.70
7 MOVING AVERAGE	1	2	.20283E+00	.76
8 MOVING AVERAGE	2	20	-.39200E+00	-13.09

THE RESIDUAL STATISTICS

SUM OF SQUARES	:	.64037E+00	DEGREES OF FREEDOM	:	979
MEAN SQUARE	:	.65411E-03	NUMBER OF RESIDUALS	:	987
R SQUARED	:	.63847E+00			

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

$$Z(t) = \text{Constant} + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) \ldots + Pi(n) * Z(t-n)$$

LAG	THE PI WEIGHT
Constant	-.10520E+02
Pi(1)	-.10126E+01
Pi(2)	-.11010E+01
Pi(3)	-.93202E+00
Pi(4)	-.72284E+00
Pi(5)	-.57645E+00
Pi(6)	-.45556E+00
Pi(7)	-.36108E+00
Pi(8)	-.28592E+00
Pi(9)	-.22648E+00
Pi(10)	-.37809E+00
Pi(11)	-.15385E+00
Pi(12)	-.88507E-01
Pi(13)	-.51511E-01
Pi(14)	-.45559E-01
Pi(15)	-.34866E-01
Pi(16)	-.27927E-01
Pi(17)	-.22039E-01
Pi(18)	-.17477E-01
Pi(19)	-.13837E-01
Pi(20)	.38104E+00
Pi(21)	.38828E+00
Pi(22)	.42473E+00
Pi(23)	.35991E+00
Pi(24)	.27904E+00
Pi(25)	.22255E+00

Pi(26)	.17588E+00
Pi(27)	.13940E+00
Pi(28)	.11039E+00
Pi(29)	.87437E-01
Pi(30)	.14715E+00
Pi(31)	.59467E-01
Pi(32)	.34027E-01
Pi(33)	.19663E-01
Pi(34)	.17440E-01
Pi(35)	.13336E-01
Pi(36)	.10685E-01
Pi(40)	-.14947E+00
Pi(41)	-.15229E+00
Pi(42)	-.16656E+00
Pi(43)	-.14114E+00
Pi(44)	-.10943E+00
Pi(45)	-.87274E-01
Pi(46)	-.68970E-01
Pi(47)	-.54666E-01
Pi(48)	-.43288E-01
Pi(49)	-.34288E-01
Pi(50)	-.57693E-01
Pi(51)	-.23319E-01
Pi(52)	-.13345E-01
Pi(60)	.58594E-01
Pi(61)	.59697E-01
Pi(62)	.65292E-01
Pi(63)	.55326E-01
Pi(64)	.42895E-01
Pi(65)	.34212E-01
Pi(66)	.27036E-01
Pi(67)	.21429E-01
Pi(68)	.16969E-01
Pi(69)	.13441E-01
Pi(70)	.22616E-01
Pi(80)	-.22969E-01
Pi(81)	-.23401E-01
Pi(82)	-.25595E-01
Pi(83)	-.21688E-01
Pi(84)	-.16815E-01
Pi(85)	-.13411E-01
Pi(86)	-.10598E-01
Pi(102)	.10033E-01

MODELING RESULTS FOR TIME SERIES AXCC212.

DATA : Z = AXCC212. 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1	MEAN		-.12358E+01	
2	AUTOREGRESSIVE 1	1	.42857E+00	4.93
3	AUTOREGRESSIVE 1	2	.24043E+00	6.31
4	MOVING AVERAGE 1	1	.34392E+00	3.88
5	MOVING AVERAGE 2	50	-.26843E+00	-8.25

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.47133E-01	DEGREES OF FREEDOM :	993
MEAN SQUARE :	.47466E-04	NUMBER OF RESIDUALS :	998
R SQUARED :	.19904E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

$$Z(t) = \text{Constant} + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) \ldots + Pi(n) * Z(t-n)$$

LAG	THE PI WEIGHT
Constant	-.24784E+01
Pi(1)	-.77249E+00
Pi(2)	-.50611E+00
Pi(3)	-.17406E+00
Pi(4)	-.59864E-01
Pi(5)	-.20588E-01
Pi(50)	.26843E+00
Pi(51)	.20736E+00
Pi(52)	.13586E+00
Pi(53)	.46724E-01
Pi(54)	.16069E-01
Pi(100)	-.72057E-01
Pi(101)	-.55664E-01
Pi(102)	-.36469E-01
Pi(103)	-.12542E-01
Pi(150)	.19343E-01
Pi(151)	.14942E-01

MODELING RESULTS FOR TIME SERIES AXCA222.

DATA : Z = AXCA222. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.18880E+01	
2 AUTOREGRESSIVE	1	2	.13944E+00	4.41
3 AUTOREGRESSIVE	1	3	.97101E-01	3.06
4 AUTOREGRESSIVE	2	10	.24565E+00	7.81
5 AUTOREGRESSIVE	2	20	.23248E+00	7.37
6 MOVING AVERAGE	1	40	-.16181E+00	-4.41

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.77204E+00	DEGREES OF FREEDOM :	971
MEAN SQUARE :	.79510E-03	NUMBER OF RESIDUALS :	977
R SQUARED :	.25175E+00		

THE RESIDUAL STATISTICS

SUM OF SQUARES : .27636E-01
MEAN SQUARE : .28142E-04
R SQUARED : .29860E+00

DEGREES OF FREEDOM : 982
NUMBER OF RESIDUALS : 987

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

$$Z(t) = \text{Constant} + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) \ldots + Pi(n) * Z(t-n)$$

LAG	THE PI WEIGHT
Constant	-.13545E+01
Pi(2)	-.32224E+00
Pi(3)	-.20626E+00
Pi(10)	.14213E+00
Pi(12)	-.45799E-01
Pi(13)	-.29316E-01
Pi(50)	.31596E+00
Pi(52)	.10181E+00
Pi(53)	.65170E-01
Pi(60)	-.44907E-01
Pi(62)	.14471E-01
Pi(100)	-.99831E-01
Pi(102)	-.32169E-01
Pi(103)	-.20591E-01
Pi(110)	.14189E-01
Pi(150)	.31543E-01
Pi(152)	.10164E-01

AUTOBJ SAMPLE PRINTOUT (SUBJECT: JJJ)

```
=========================================================================
MODELING RESULTS FOR TIME SERIES JJJAATRE
=========================================================================

     ***************************************************************
     DATA :    Z = JJJAATRE    1000.                1000 OBSERVATIONS

     DIFFERENCING ON   Z : 1) 1 OF ORDER  1

     BACKCASTING : OFF
     ***************************************************************
     UNIVARIATE MODEL PARAMETERS
     ***************************************************************
                   FACTOR   LAG COEFFICIENT       T RATIO

     ***************************************************************
      1 AUTOREGRESSIVE 1    20   .19333E+00          6.07
      2 MOVING AVERAGE 1     1   .97558E+00         41.12
      3 MOVING AVERAGE 1     3  -.66148E-01         -2.67
      4 MOVING AVERAGE 2    50  -.17422E+00         -5.36
     ***************************************************************

                        THE RESIDUAL STATISTICS
                        =======================

  SUM OF SQUARES :  .48252E+01          DEGREES OF FREEDOM  :      975
  MEAN SQUARE    :  .49489E-02          NUMBER OF RESIDUALS :      979
  R SQUARED      :  .68648E+00



                             THE PI WEIGHTS
                             ==============

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST
PLUS A RANDOM SHOCK.  DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE
TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO  OTHER TYPES OF MODELS.

      THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

  Z(t)  =  Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)
```

LAG	THE PI WEIGHT
Constant	.00000E+00
Pi(1)	-.19756E+01
Pi(2)	-.19273E+01
Pi(3)	-.18141E+01
Pi(4)	-.16391E+01
Pi(5)	-.14716E+01
Pi(6)	-.13157E+01
Pi(7)	-.11751E+01
Pi(8)	-.10491E+01
Pi(9)	-.93643E+00
Pi(10)	-.83583E+00
Pi(11)	-.74602E+00
Pi(12)	-.66586E+00
Pi(13)	-.59431E+00
Pi(14)	-.53045E+00
Pi(15)	-.47345E+00
Pi(16)	-.42258E+00
Pi(17)	-.37717E+00
Pi(18)	-.33664E+00
Pi(19)	-.30047E+00
Pi(20)	-.46151E+00
Pi(21)	-.23464E+00
Pi(22)	-.20904E+00
Pi(23)	-.17340E+00
Pi(24)	-.15365E+00
Pi(25)	-.13607E+00
Pi(26)	-.12127E+00
Pi(27)	-.10815E+00
Pi(28)	-.96508E-01
Pi(29)	-.86129E-01
Pi(30)	-.76872E-01
Pi(31)	-.68611E-01
Pi(32)	-.61238E-01
Pi(33)	-.54657E-01
Pi(34)	-.48784E-01
Pi(35)	-.43542E-01
Pi(36)	-.38863E-01
Pi(37)	-.34687E-01
Pi(38)	-.30960E-01
Pi(39)	-.27633E-01
Pi(40)	-.24664E-01
Pi(41)	-.22014E-01
Pi(42)	-.19648E-01
Pi(43)	-.17537E-01
Pi(44)	-.15652E-01
Pi(45)	-.13970E-01
Pi(46)	-.12469E-01
Pi(47)	-.11129E-01
Pi(50)	.16631E+00

Pi(51)	.33712E+00
Pi(52)	.32948E+00
Pi(53)	.31043E+00
Pi(54)	.28055E+00
Pi(55)	.25190E+00
Pi(56)	.22522E+00
Pi(57)	.20116E+00
Pi(58)	.17958E+00
Pi(59)	.16030E+00
Pi(60)	.14308E+00
Pi(61)	.12771E+00
Pi(62)	.11398E+00
Pi(63)	.10174E+00
Pi(64)	.90804E-01
Pi(65)	.81046E-01
Pi(66)	.72338E-01
Pi(67)	.64565E-01
Pi(68)	.57627E-01
Pi(69)	.51434E-01
Pi(70)	.79589E-01
Pi(71)	.40152E-01
Pi(72)	.35769E-01
Pi(73)	.29631E-01
Pi(74)	.26251E-01
Pi(75)	.23244E-01
Pi(76)	.20717E-01
Pi(77)	.18474E-01
Pi(78)	.16485E-01
Pi(79)	.14713E-01
Pi(80)	.13131E-01
Pi(81)	.11720E-01
Pi(82)	.10461E-01
Pi(100)	-.29001E-01
Pi(101)	-.58757E-01
Pi(102)	-.57423E-01
Pi(103)	-.54102E-01
Pi(104)	-.48894E-01
Pi(105)	-.43902E-01
Pi(106)	-.39251E-01
Pi(107)	-.35058E-01
Pi(108)	-.31298E-01
Pi(109)	-.27937E-01
Pi(110)	-.24936E-01
Pi(111)	-.22257E-01
Pi(112)	-.19865E-01
Pi(113)	-.17731E-01
Pi(114)	-.15825E-01
Pi(115)	-.14125E-01
Pi(116)	-.12607E-01
Pi(117)	-.11252E-01
Pi(118)	-.10043E-01
Pi(120)	-.13869E-01
Pi(151)	.10237E-01
Pi(152)	.10004E-01

MODELING RESULTS FOR TIME SERIES JJJCATRE

DATA : Z = JJJCATRE 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : 1) 1 OF ORDER 10

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 AUTOREGRESSIVE	1	10	-.68971E+00	-24.07
2 MOVING AVERAGE	1	1	.28697E+00	9.47
3 MOVING AVERAGE	1	3	-.17975E+00	-5.92
4 MOVING AVERAGE	2	20	.43790E+00	12.25
5 TREND CONSTANT			-.81478E-03	-7.61

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.38776E-01	DEGREES OF FREEDOM :	975
MEAN SQUARE :	.39770E-04	NUMBER OF RESIDUALS :	980
R SQUARED :	.84003E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.16236E-02
Pi(1)	-.28697E+00
Pi(2)	-.82350E-01
Pi(3)	.15612E+00
Pi(4)	.96383E-01
Pi(5)	.42461E-01
Pi(6)	-.15877E-01
Pi(7)	-.21881E-01
Pi(8)	-.13912E-01
Pi(10)	-.30668E+00
Pi(11)	-.85507E-01
Pi(12)	-.24333E-01
Pi(13)	.48143E-01
Pi(14)	.29185E-01
Pi(15)	.12749E-01
Pi(20)	-.11265E+01
Pi(21)	-.32251E+00
Pi(22)	-.92495E-01
Pi(23)	.17595E+00
Pi(24)	.10846E+00
Pi(25)	.47751E-01
Pi(26)	-.17923E-01
Pi(27)	-.24639E-01
Pi(28)	-.15654E-01
Pi(30)	-.13181E+00
Pi(31)	-.35011E-01
Pi(33)	.20875E-01
Pi(34)	.12284E-01
Pi(40)	-.49329E+00
Pi(41)	-.14124E+00
Pi(42)	-.40513E-01
Pi(43)	.77044E-01
Pi(44)	.47497E-01
Pi(45)	.20912E-01
Pi(47)	-.10790E-01
Pi(50)	-.57719E-01
Pi(51)	-.15331E-01
Pi(60)	-.21600E+00
Pi(61)	-.61845E-01
Pi(62)	-.17748E-01
Pi(63)	.33733E-01
Pi(64)	.20797E-01
Pi(70)	-.25275E-01
Pi(80)	-.94585E-01
Pi(81)	-.27082E-01
Pi(83)	.14771E-01
Pi(90)	-.11068E-01
Pi(100)	-.41418E-01
Pi(101)	-.11859E-01
Pi(120)	-.18156E-01

```
=================================================================================
MODELING RESULTS FOR TIME SERIES JJJA111.
=================================================================================

     ****************************************************************
     DATA :   Z = JJJA111.   1000.                   1000 OBSERVATIONS

     DIFFERENCING ON   Z : NONE

     BACKCASTING : OFF
     ****************************************************************
     UNIVARIATE MODEL PARAMETERS
     ****************************************************************
                   FACTOR   LAG COEFFICIENT      T RATIO

     ****************************************************************
      1 MEAN                      .13158E+01
      2 AUTOREGRESSIVE 1      1  -.50671E+00       -16.46
      3 AUTOREGRESSIVE 1      2  -.26687E+00        -8.67
      4 AUTOREGRESSIVE 1      4   .60035E-01         2.11
      5 AUTOREGRESSIVE 2     10   .29674E+00         9.58
      6 MOVING AVERAGE 1     30  -.13514E+00        -4.11
     ****************************************************************
                        THE RESIDUAL STATISTICS
                        =======================

   SUM OF SQUARES :  .57848E+01         DEGREES OF FREEDOM   :     980
   MEAN SQUARE    :  .59029E-02         NUMBER OF RESIDUALS  :     986
   R SQUARED      :  .30725E+00


                           THE PI WEIGHTS
                           ==============
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UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	.92142E+00
Pi(1)	.50671E+00
Pi(2)	.26687E+00
Pi(4)	-.60035E-01
Pi(10)	-.29674E+00
Pi(11)	-.15036E+00
Pi(12)	-.79191E-01
Pi(14)	.17814E-01
Pi(30)	.13514E+00
Pi(31)	-.68478E-01
Pi(32)	-.36066E-01
Pi(40)	.40101E-01
Pi(41)	.20320E-01
Pi(42)	.10702E-01
Pi(60)	-.18263E-01

MODELING RESULTS FOR TIME SERIES JJJC111.

DATA : Z = JJJC111. 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.29826E+01	
2 AUTOREGRESSIVE	1	1	.84105E-01	2.66
3 AUTOREGRESSIVE	1	2	.25509E+00	8.30
4 AUTOREGRESSIVE	1	3	.17367E+00	5.49
5 AUTOREGRESSIVE	2	10	.11135E+00	3.49

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.89756E-01	DEGREES OF FREEDOM :	982
MEAN SQUARE :	.91401E-04	NUMBER OF RESIDUALS :	987
R SQUARED :	.13713E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.46740E+01
Pi(1)	-.84105E-01
Pi(2)	-.25509E+00
Pi(3)	-.17367E+00
Pi(10)	-.11135E+00
Pi(12)	.28405E-01
Pi(13)	.19339E-01

MODELING RESULTS FOR TIME SERIES JJJA121.

DATA : Z = JJJA121. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			.12344E+01	
2 AUTOREGRESSIVE	1	1	-.54072E+00	-17.60
3 AUTOREGRESSIVE	1	2	-.27013E+00	-8.79
4 AUTOREGRESSIVE	2	10	.66750E+00	25.10
5 MOVING AVERAGE	1	20	-.16508E+00	-4.57

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.29880E+01	DEGREES OF FREEDOM :	983
MEAN SQUARE :	.30397E-02	NUMBER OF RESIDUALS :	988
R SQUARED :	.66930E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	.14810E+01
Pi(1)	.54072E+00
Pi(2)	.27013E+00
Pi(10)	-.66750E+00
Pi(11)	-.36093E+00
Pi(12)	-.18031E+00
Pi(20)	.16508E+00
Pi(21)	-.89262E-01
Pi(22)	-.44592E-01
Pi(30)	.11019E+00
Pi(31)	.59582E-01
Pi(32)	.29765E-01
Pi(40)	-.27251E-01
Pi(41)	.14735E-01
Pi(50)	-.18190E-01

MODELING RESULTS FOR TIME SERIES JJJC121.

DATA : Z = JJJC121. 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1	MEAN		-.29711E+01	
2	AUTOREGRESSIVE 1	2	.14048E+00	4.45
3	AUTOREGRESSIVE 1	3	.16761E+00	5.38
4	AUTOREGRESSIVE 1	4	.79626E-01	2.52
5	AUTOREGRESSIVE 2	10	.93544E-01	2.93
6	AUTOREGRESSIVE 2	20	.15126E+00	4.76
7	MOVING AVERAGE 1	30	-.14436E+00	-4.44

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.12944E+00	DEGREES OF FREEDOM :	963
MEAN SQUARE :	.13358E-03	NUMBER OF RESIDUALS :	976
R SQUARED :	.11919E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.39921E+01
Pi(2)	-.14048E+00
Pi(3)	-.16761E+00
Pi(4)	-.79626E-01
Pi(10)	-.93544E-01
Pi(12)	.13141E-01
Pi(13)	.15679E-01
Pi(20)	-.15126E+00
Pi(22)	.21249E-01
Pi(23)	.25352E-01
Pi(24)	.12044E-01
Pi(30)	.14436E+00
Pi(32)	.20280E-01
Pi(33)	.24195E-01
Pi(34)	.11495E-01
Pi(40)	.13504E-01
Pi(50)	.21835E-01
Pi(60)	-.20839E-01

MODELING RESULTS FOR TIME SERIES JJJA211.

DATA : Z = JJJA211. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			.13154E+01	
2 AUTOREGRESSIVE	1	10	.25098E+00	7.96
3 AUTOREGRESSIVE	1	20	.17444E+00	5.62
4 MOVING AVERAGE	1	1	.42855E+00	13.42
5 MOVING AVERAGE	1	2	.73318E-01	2.11
6 MOVING AVERAGE	1	3	-.90160E-01	-2.80
7 MOVING AVERAGE	2	40	-.69039E-01	-2.12

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.50976E+01	DEGREES OF FREEDOM :	973
MEAN SQUARE :	.52391E-02	NUMBER OF RESIDUALS :	980
R SQUARED :	.27477E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	.29814E+01
Pi(1)	-.42855E+00
Pi(2)	-.25697E+00
Pi(3)	-.51387E-01
Pi(5)	.18448E-01
Pi(6)	.12376E-01
Pi(10)	-.25130E+00
Pi(11)	-.10787E+00
Pi(12)	-.64681E-01
Pi(13)	-.12971E-01
Pi(20)	-.17456E+00
Pi(21)	-.74856E-01
Pi(22)	-.44878E-01
Pi(40)	.69039E-01
Pi(41)	.29587E-01
Pi(42)	.17741E-01
Pi(50)	.17359E-01
Pi(60)	.12054E-01

MODELING RESULTS FOR TIME SERIES JJJC211.

DATA : Z = JJJC211. 10000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.21062E+01	
2 AUTOREGRESSIVE	1	1	.10464E+00	3.32
3 AUTOREGRESSIVE	1	2	.20754E+00	6.71
4 AUTOREGRESSIVE	1	3	.17823E+00	5.65
5 AUTOREGRESSIVE	2	10	.14339E+00	4.46
6 AUTOREGRESSIVE	2	20	.12431E+00	3.86
7 MOVING AVERAGE	1	30	-.10870E+00	-3.29

THE RESIDUAL STATISTICS

SUM OF SQUARES : .10776E+00
MEAN SQUARE : .11109E-03
R SQUARED : .16005E+00

DEGREES OF FREEDOM : 970
NUMBER OF RESIDUALS : 977

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.30905E+01
Pi(1)	-.10464E+00
Pi(2)	-.20754E+00
Pi(3)	-.17823E+00
Pi(10)	-.14339E+00
Pi(11)	.15004E-01
Pi(12)	.29759E-01
Pi(13)	.25558E-01
Pi(20)	-.12431E+00
Pi(21)	.13008E-01
Pi(22)	.25800E-01
Pi(23)	.22157E-01
Pi(30)	.10870E+00
Pi(31)	.11374E-01
Pi(32)	.22560E-01
Pi(33)	.19374E-01
Pi(40)	.15587E-01
Pi(50)	.13513E-01
Pi(60)	-.11816E-01

MODELING RESULTS FOR TIME SERIES JJJA221.

DATA : Z = JJJA221. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.13395E+01	
2 AUTOREGRESSIVE	1	2	.11956E+00	3.65
3 AUTOREGRESSIVE	1	3	.29663E+00	9.73
4 AUTOREGRESSIVE	1	4	.20041E+00	6.58
5 AUTOREGRESSIVE	2	10	.49611E+00	16.34
6 MOVING AVERAGE	1	1	.46162E+00	14.44
7 MOVING AVERAGE	2	30	-.23880E+00	-7.47

THE RESIDUAL STATISTICS

SUM OF SQUARES : .58201E+01
MEAN SQUARE : .59449E-02
R SQUARED : .56236E+00

DEGREES OF FREEDOM : 979
NUMBER OF RESIDUALS : 986

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

$$Z(t) = \text{Constant} + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) \ldots + Pi(n) * Z(t-n)$$

LAG	THE PI WEIGHT
Constant	-.36289E+01
Pi(1)	-.46162E+00
Pi(2)	-.33266E+00
Pi(3)	-.45019E+00
Pi(4)	-.40822E+00
Pi(5)	-.18844E+00
Pi(6)	-.86990E-01
Pi(7)	-.40157E-01
Pi(8)	-.18537E-01
Pi(10)	-.50006E+00
Pi(11)	-.23084E+00
Pi(12)	-.47245E-01
Pi(13)	.12535E+00
Pi(14)	.15729E+00
Pi(15)	.72608E-01
Pi(16)	.33517E-01
Pi(17)	.15472E-01
Pi(30)	.23880E+00
Pi(31)	.11023E+00
Pi(32)	.79437E-01
Pi(33)	.10750E+00
Pi(34)	.97482E-01
Pi(35)	.45000E-01
Pi(36)	.20773E-01
Pi(40)	.11941E+00
Pi(41)	.55124E-01
Pi(42)	.11282E-01
Pi(43)	-.29933E-01
Pi(44)	-.37560E-01
Pi(45)	-.17339E-01
Pi(60)	-.57024E-01
Pi(61)	-.26323E-01
Pi(62)	-.18969E-01
Pi(63)	-.25671E-01
Pi(64)	-.23278E-01
Pi(65)	-.10746E-01
Pi(70)	-.28516E-01
Pi(71)	-.13163E-01
Pi(90)	.13617E-01

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=============================================================================
MODELING RESULTS FOR TIME SERIES JJJC221.
=============================================================================

     ******************************************************************
     DATA :    Z = JJJC221.   10000.                 1000 OBSERVATIONS

     DIFFERENCING ON    Z : NONE

     BACKCASTING : OFF
     ******************************************************************
     UNIVARIATE MODEL PARAMETERS
     ******************************************************************
                    FACTOR   LAG COEFFICIENT        T RATIO

     ******************************************************************
      1 MEAN                     -.19154E+01
      2 AUTOREGRESSIVE 1      2   .14333E+00         4.58
      3 AUTOREGRESSIVE 1      3   .13359E+00         4.27
      4 AUTOREGRESSIVE 2     10   .71010E-01         2.23
      5 MOVING AVERAGE 1     70  -.86921E-01        -2.65
     ******************************************************************

                           THE RESIDUAL STATISTICS
                           =======================

   SUM OF SQUARES :  .12971E+00          DEGREES OF FREEDOM   :      982
   MEAN SQUARE    :  .13209E-03          NUMBER OF RESIDUALS  :      987
   R SQUARED      :  .52182E-01


                              THE PI WEIGHTS
                              ==============

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST
PLUS A RANDOM SHOCK.  DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE
TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO  OTHER TYPES OF MODELS.

      THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

  Z(t)  =  Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)
```

LAG	THE PI WEIGHT
Constant	-.23407E+01
Pi(2)	-.14333E+00
Pi(3)	-.13359E+00
Pi(10)	-.71010E-01
Pi(12)	.10178E-01
Pi(70)	.86921E-01
Pi(72)	.12459E-01
Pi(73)	.11612E-01

MODELING RESULTS FOR TIME SERIES JJJA212.

DATA : Z = JJJA212. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1	MEAN		-.53939E+01	
2	AUTOREGRESSIVE 1	1	-.58550E+00	-19.76
3	AUTOREGRESSIVE 1	2	-.37125E+00	-12.54
4	AUTOREGRESSIVE 2	10	.89172E+00	45.31
5	MOVING AVERAGE 1	10	.49908E+00	13.08

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.58862E+01	DEGREES OF FREEDOM :	983
MEAN SQUARE :	.59880E-02	NUMBER OF RESIDUALS :	988
R SQUARED :	.66509E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.19254E+02
Pi(1)	.58550E+00
Pi(2)	.37125E+00
Pi(10)	-.13908E+01
Pi(11)	-.22989E+00
Pi(12)	-.14577E+00
Pi(20)	-.69411E+00
Pi(21)	-.11473E+00
Pi(22)	-.72749E-01
Pi(30)	-.34641E+00
Pi(31)	-.57260E-01
Pi(32)	-.36307E-01
Pi(40)	-.17289E+00
Pi(41)	-.28577E-01
Pi(42)	-.18120E-01
Pi(50)	-.86283E-01
Pi(51)	-.14262E-01
Pi(60)	-.43062E-01
Pi(70)	-.21491E-01
Pi(80)	-.10726E-01

MODELING RESULTS FOR TIME SERIES JJJC212.

DATA : Z = JJJC212. 100. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.60968E+01	
2 AUTOREGRESSIVE	1	1	.10810E+00	3.37
3 AUTOREGRESSIVE	1	2	.25623E+00	8.32
4 AUTOREGRESSIVE	1	3	.14199E+00	4.49
5 AUTOREGRESSIVE	2	10	.24591E+00	7.75
6 AUTOREGRESSIVE	2	20	.13294E+00	4.18
7 MOVING AVERAGE	1	50	-.84624E-01	-2.53

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.73506E+03	DEGREES OF FREEDOM :	970
MEAN SQUARE :	.75779E+00	NUMBER OF RESIDUALS :	977
R SQUARED :	.18459E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.95185E+01
Pi(1)	-.10810E+00
Pi(2)	-.25623E+00
Pi(3)	-.14199E+00
Pi(10)	-.24591E+00
Pi(11)	.26583E-01
Pi(12)	.63011E-01
Pi(13)	.34917E-01
Pi(20)	-.13294E+00
Pi(21)	.14370E-01
Pi(22)	.34063E-01
Pi(23)	.18876E-01
Pi(50)	.84624E-01
Pi(52)	.21684E-01
Pi(53)	.12016E-01
Pi(60)	.20810E-01
Pi(70)	.11250E-01

MODELING RESULTS FOR TIME SERIES JJJA222.

DATA : Z = JJJA222. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.58224E+01	
2 AUTOREGRESSIVE	1	1	.58105E-01	1.86
3 AUTOREGRESSIVE	1	3	.20355E+00	6.47
4 AUTOREGRESSIVE	2	10	.87782E+00	45.61
5 MOVING AVERAGE	1	2	-.13798E+00	-4.36
6 MOVING AVERAGE	2	10	.29425E+00	7.61

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.49844E+00	DEGREES OF FREEDOM :	981
MEAN SQUARE :	.50810E-03	NUMBER OF RESIDUALS :	987
R SQUARED :	.62802E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

$$Z(t) = \text{Constant} + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) \ldots + Pi(n) * Z(t-n)$$

LAG	THE PI WEIGHT
Constant	-.13845E+02
Pi(1)	-.58105E-01
Pi(2)	.13798E+00
Pi(3)	-.19553E+00
Pi(4)	-.19038E-01
Pi(5)	.26979E-01
Pi(10)	-.11720E+01
Pi(11)	.33837E-01
Pi(12)	.16171E+00
Pi(13)	.11411E+00
Pi(14)	-.22313E-01
Pi(15)	-.15745E-01
Pi(20)	-.34483E+00
Pi(21)	.10019E-01
Pi(22)	.47578E-01
Pi(23)	.33569E-01
Pi(30)	-.10147E+00
Pi(32)	.14000E-01
Pi(40)	-.29862E-01

MODELING RESULTS FOR TIME SERIES JJJC222.

DATA : Z = JJJC222. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			.73183E+00	
2 AUTOREGRESSIVE	1	1	-.97088E-01	-3.05
3 AUTOREGRESSIVE	1	2	.18436E+00	5.87
4 AUTOREGRESSIVE	1	3	.17600E+00	5.53
5 AUTOREGRESSIVE	2	10	.21626E+00	6.75
6 AUTOREGRESSIVE	2	30	.15128E+00	4.74
7 MOVING AVERAGE	1	20	-.15290E+00	-4.62

THE RESIDUAL STATISTICS

SUM OF SQUARES	.11133E+02	DEGREES OF FREEDOM	960
MEAN SQUARE	.11597E-01	NUMBER OF RESIDUALS	967
R SQUARED	.16219E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

$$Z(t) = \text{Constant} + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) \ldots + Pi(n) * Z(t-n)$$

LAG	THE PI WEIGHT
Constant	.97376E+00
Pi(1)	.97088E-01
Pi(2)	-.18436E+00
Pi(3)	-.17600E+00
Pi(10)	-.21626E+00
Pi(11)	-.20996E-01
Pi(12)	.39869E-01
Pi(13)	.38060E-01
Pi(20)	.15290E+00
Pi(21)	-.14845E-01
Pi(22)	.28188E-01
Pi(23)	.26910E-01
Pi(30)	-.11821E+00
Pi(31)	-.11477E-01
Pi(32)	.21794E-01
Pi(33)	.20805E-01
Pi(40)	-.23378E-01
Pi(50)	.18075E-01

MODELING RESULTS FOR TIME SERIES JJJA112.

DATA : Z = JJJA112. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1	MEAN		-.67906E+01	
2	AUTOREGRESSIVE 1	1	-.26564E+00	-8.68
3	AUTOREGRESSIVE 2	10	.52048E+00	17.31
4	MOVING AVERAGE 1	20	-.17211E+00	-4.96

THE RESIDUAL STATISTICS

SUM OF SQUARES	: .19409E+01		DEGREES OF FREEDOM	: 985
MEAN SQUARE	: .19705E-02		NUMBER OF RESIDUALS	: 989
R SQUARED	: .36941E+00			

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.80709E+01
Pi(1)	.26564E+00
Pi(10)	-.52048E+00
Pi(11)	-.13826E+00
Pi(20)	.17211E+00
Pi(21)	-.45719E-01
Pi(30)	.89580E-01
Pi(31)	.23796E-01
Pi(40)	-.29622E-01
Pi(50)	-.15418E-01

MODELING RESULTS FOR TIME SERIES JJJC112.

DATA : Z = JJJC112. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			.63113E+01	
2 AUTOREGRESSIVE	1	1	.79309E-01	2.48
3 AUTOREGRESSIVE	1	2	.21900E+00	7.04
4 AUTOREGRESSIVE	1	3	.16608E+00	5.19
5 AUTOREGRESSIVE	2	10	.26382E+00	8.15
6 AUTOREGRESSIVE	2	20	.20279E+00	6.29
7 MOVING AVERAGE	1	30	-.83247E-01	-2.44

THE RESIDUAL STATISTICS

SUM OF SQUARES :	.74056E+01	DEGREES OF FREEDOM :	970
MEAN SQUARE :	.76347E-02	NUMBER OF RESIDUALS :	977
R SQUARED :	.22761E+00		

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	.99881E+01
Pi(1)	-.79309E-01
Pi(2)	-.21900E+00
Pi(3)	-.16608E+00
Pi(10)	-.26382E+00
Pi(11)	.20923E-01
Pi(12)	.57775E-01
Pi(13)	.43816E-01
Pi(20)	-.20279E+00
Pi(21)	.16083E-01
Pi(22)	.44410E-01
Pi(23)	.33680E-01
Pi(30)	.83247E-01
Pi(32)	.18231E-01
Pi(33)	.13826E-01
Pi(40)	.21962E-01
Pi(50)	.16881E-01

MODELING RESULTS FOR TIME SERIES JJJA122.

DATA : Z = JJJA122. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			-.68009E+01	
2 AUTOREGRESSIVE	1	10	.64461E+00	26.11
3 MOVING AVERAGE	1	1	.26997E+00	8.78
4 MOVING AVERAGE	2	50	.11061E+00	3.34

THE RESIDUAL STATISTICS

SUM OF SQUARES : .18079E+01 DEGREES OF FREEDOM : 986
MEAN SQUARE : .18336E-02 NUMBER OF RESIDUALS : 990
R SQUARED : .43978E+00

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

Z(t) = Constant + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) ... + Pi(n) * Z(t-n)

LAG	THE PI WEIGHT
Constant	-.17226E+02
Pi(1)	-.26997E+00
Pi(2)	-.72886E-01
Pi(3)	-.19677E-01
Pi(10)	-.64461E+00
Pi(11)	-.17403E+00
Pi(12)	-.46983E-01
Pi(13)	-.12684E-01
Pi(50)	-.11061E+00
Pi(51)	-.29861E-01
Pi(60)	-.71298E-01
Pi(61)	-.19248E-01
Pi(100)	-.12234E-01

MODELING RESULTS FOR TIME SERIES JJJC122.

DATA : Z = JJJC122. 1000. 1000 OBSERVATIONS

DIFFERENCING ON Z : NONE

BACKCASTING : OFF

UNIVARIATE MODEL PARAMETERS

	FACTOR	LAG	COEFFICIENT	T RATIO
1 MEAN			.66319E+01	
2 AUTOREGRESSIVE	1	1	-.12195E+00	-3.88
3 AUTOREGRESSIVE	1	2	.15636E+00	4.99
4 AUTOREGRESSIVE	1	3	.18918E+00	6.01
5 AUTOREGRESSIVE	2	10	.13376E+00	4.20
6 AUTOREGRESSIVE	2	20	.15959E+00	5.00
7 MOVING AVERAGE	1	30	-.12349E+00	-3.77

THE RESIDUAL STATISTICS

SUM OF SQUARES : .14183E+02
MEAN SQUARE : .14622E-01
R SQUARED : .12877E+00

DEGREES OF FREEDOM : 970
NUMBER OF RESIDUALS : 977

THE PI WEIGHTS

UNIVARIATE BOX-JENKINS MODELS CAN BE EXPRESSED AS A WEIGHTED SUM OF THE PAST PLUS A RANDOM SHOCK. DEFINED AS THE PI WEIGHTS, MODELS EXPRESSED IN THESE TERMS ARE USEFUL FOR FORECASTING AND/OR COMPARISON TO OTHER TYPES OF MODELS.

THE GENERAL FORM OF THE MODEL EXPRESSED BY THE PI WEIGHTS IS :

$$Z(t) = \text{Constant} + Pi(1) * Z(t-1) + Pi(2) * Z(t-2) \ldots + Pi(n) * Z(t-n)$$

LAG	THE PI WEIGHT
Constant	.85672E+01
Pi(1)	.12195E+00
Pi(2)	-.15636E+00
Pi(3)	-.18918E+00
Pi(10)	-.13376E+00
Pi(11)	-.16312E-01
Pi(12)	.20915E-01
Pi(13)	.25304E-01
Pi(20)	-.15959E+00
Pi(21)	-.19462E-01
Pi(22)	.24953E-01
Pi(23)	.30190E-01
Pi(30)	.12349E+00
Pi(31)	-.15060E-01
Pi(32)	.19309E-01
Pi(33)	.23362E-01
Pi(40)	.16518E-01
Pi(50)	.19707E-01
Pi(60)	-.15250E-01

END

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